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INDIAN CURRENCY FAKE NOTE DETECTION SYSTEM USING DEEP NEURAL NETWORK

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Abstract: The development of color printing technology has accelerated the manufacture and duplication of false Indian rupee notes on a big scale. A few years ago, printing could only be done in a print shop, but now anyone with a cheap laser printer can print a currency note with utmost accuracy. As a result, the use of counterfeit notes in place of legitimate ones has skyrocketed. We require a technique to determine if a money note is genuine or counterfeit. We employ the Convolutional Neural Network method and image processing to determine whether a letter is genuine or a forgery. These algorithms and image processing are used to execute data processing and data extraction, resulting in an accurate result. To identify the money in the current system Is the note genuine or a forgery? It makes use of SVM (Support Vector Machine). When you have a small dataset with noise-free and labelled data, SVM is utilised for data processing. The SVM algorithm does not work well on huge datasets, and the results of the SVM algorithm are limited due to the short data set employed. When put into a real-world situation, it does not perform as well as it does now. Because of the vast data sets, the system is sluggish, has low accuracy, and consumes a lot of memory. The suggested method would evaluate the differences between a fake and a real note. Image processing introduces numerous machine learning techniques that offer the false identity of a person in the modern era of computer science and high computational approaches. the monetary unit Color, form, paper width, and image filtering on the note are among the entities detected and recognized by the algorithm. Using a Convolutional Neural Network and image processing, developing a method for detecting bogus cash. It finds the relevant traits without the need for human intervention. This technique can quickly distinguish between a fake and a genuine note. It will express the outcome in text, such as the note's worth and if it is false or genuine.

Index Terms - Convolution neural network, SVM, Image Processing, counterfeit.

I. INTRODUCTION

Paper money is still one of the most used methods for exchanging goods and services today. One of the lingering issues is the identification of counterfeit banknotes, which are becoming more similar to originals, making it harder for non-experts to detect them. On the other side, there are devices that can identify counterfeit banknotes; however, because these equipment are frequently expensive, the detection and retention of counterfeits is left to banking and government agencies, with little community engagement. There are approaches based on traditional computer vision techniques in the state-of-the-art to tackle this problem and provide alternate alternatives. Histogram equalisation, closest neighbour interpolation, evolutionary algorithms, and fuzzy systems are just a few examples. However, the fundamental drawback of these approaches is their limited ability to generalize to new samples as well as their low accuracy. Another group includes deep learning (DL) approaches that use convolutional neural networks (CNNs), which have outperformed both traditional machine learning techniques and humans. In tasks requiring categorization.

There are several ideas in the domain of banknote recognition and counterfeit detection, given the present prominence of CNNs in the field of computer vision.The approach employs the notion of transfer learning, in which a deep convolutional neural network that has previously been trained on a large dataset of natural pictures is repurposed to solve the problem of banknote image classification. To learn the new classes connected with the challenge, actual photos of banknotes collected under varying lighting conditions are input to a custom designed neural network topped atop a pre-trained convolution basis. On a held-out testing subset, the resultant classifier achieves a considerable accuracy of 96.6 percent after being trained on a relatively sized dataset. The approach necessitates pre-processing of photos before feeding them to the classifier, and it works well for recognition even when there is clutter in the back drop. Through the auto mated system, which is a convolution neural network in deep learning, this system is utilised to determine whether the cash is false or original. Deep learning is very good at recognising and classifying images over big data sets, and it's also used a lot in object category recognition. Although the current demonetization push is a step toward eradicating corruption and black money, it does not address the issue of counterfeit cash. A deep neural network (Figure) is a computer model that mimics the way neurons in the human brain operate. Each neuron receives an input, performs certain processes, and then transmits the result to the next neuron in the buried layer. It's still impossible to tell if a money note is phoney just by looking at it. Because the ordinary person is unaware of all of the security mechanisms inherent in a currency note, he or she is prone to fraud. One interesting approach to tackling this challenge is to combine a low-cost algorithm with low-cost apps that can detect a phoney cash note through an image. The similar method may be implemented in smart-phones for future work.

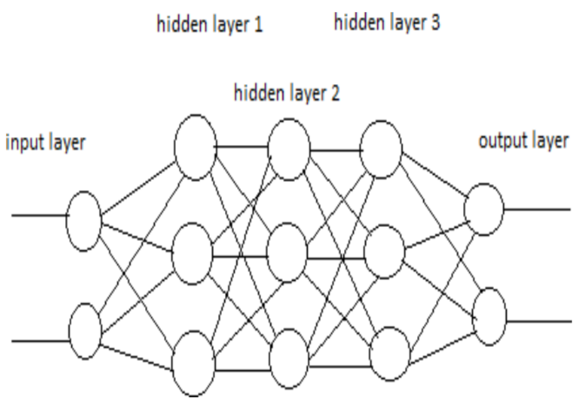


Figure 1: A Deep Neural Network

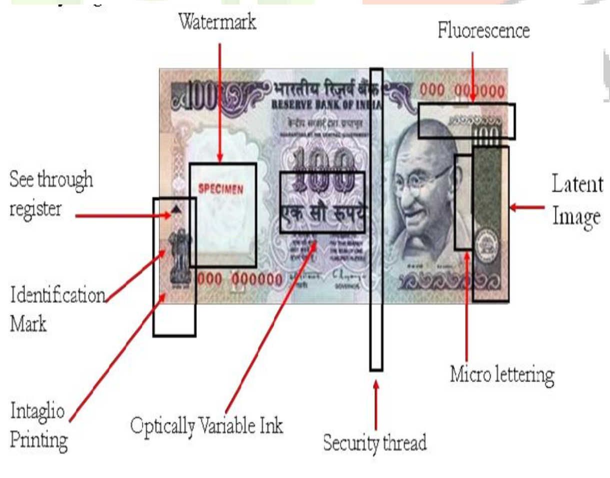
II. Related work

Concerns have recently been raised concerning the money acknowledgement system as a result of an increase in the spread of counterfeit money. As a result, the goal of any cash acknowledgement system is to locate the counterfeit money. A successful method for differentiating paper money entails a series of steps: first, capture an image, then transform to grayscale, identify edges, division, highlight extraction, and picture correlation. Currently, I'm looking at several types of literature that depict various approaches for detecting false monetary standards. The repository also includes a schematic of how to identify bogus Indian currency for extortion identification. Most banknotes have anti-counterfeit features that may be exposed to different light wavelengths to detect counterfeiting. For recording the optical features of the banknotes investigated, previous efforts on fake banknote identification employed a mix of several sensor types or single sensors. For counterfeit detection, RGB colour and UV information were used to compare reference and input banknotes. suggested a counterfeit banknote detection method based on low-resolution multispectral pictures containing RGB images on both sides and three-frequency IR images. For limited-resource devices, Kang and Lee employed multispectral pictures with linear and quadratic classifiers. Break et al. Used the same multispectral banknote image capture approach. For detecting phoney banknotes, researchers employed neural networks, a probability test, and a parallelepiped classification algorithm. Han and Kim suggested a technique that employs aligned visible-light, IR reflection, and IR transmission pictures of banknotes as input data for a convolutional neural network (CNN) classifier to detect counterfeits. A range of wavelengths were examined for recording banknote pictures in research employing single sensors, ranging from IR, visible light, to UV. Previous research using image sensors with wavelengths outside of visible light focused on collecting security characteristics such as latent patterns on Indian banknotes under UV light or dark and bright spots on Euro banknotes under IR light. For counterfeit coin detection and banknote pigment-based counterfeit detection, X-rays were also explored. These counterfeit detection techniques presuppose that either the denomination and input direction of banknotes are known, or that pre-recognition of the banknote type is necessary, since security elements are situated at certain locations on banknotes. For counterfeit detection, visible-light techniques were largely relied on the colour properties of banknotes. For counterfeit note identification, the brightness histogram of the Y channel in the YIQ colour space of the scanned banknote image was employed. This sort of characteristic was also utilised to suggest a way for imaging banknotes using a camera while they were put on a backlight panel. The support vector machine (SVM) was utilised as the classifier in each of these investigations. CNN has recently been widely employed to tackle a variety of problems because to its efficiency. Studies on automatic banknote sorting utilising CNN, such as banknote recognition fitness categorization or serial number recognition, have also been conducted. CNN has also been used to identify fraudulent banknotes. Using CNN on randomly cropped pictures from banknotes, the approach suggested in can detect phoney banknotes and the scanning machines used to create them. CNN was used to categorise photographs of fraudulent and genuine banknotes acquired from various sources on the internet, and it was suggested that the proposed approach be implemented using a smartphone. The experiments in these papers utilised Indian rupee (INR) banknotes, although the authors did not specify the denomination or input direction of the banknote pictures used in the experimental datasets. The CNN-based system published in proved successful for both banknote type recognition and counterfeit detection, however it employed a mix of photos for each banknote, including visible-light, IR reflection, and IR transmission images. We suggested a false banknote classification approach utilising CNN on banknote pictures acquired by smartphone cameras under visible-light settings based on a study of the advantages and shortcomings of existing systems. We started by locating the picture region containing the banknote and cropping it as the region of interest (ROI) based on the selected image's centre. This procedure lowers the impact of the acquired image's backdrop, which can influence classification accuracy. The ROIs were then utilised as inputs for CNN models to classify real and fraudulent banknotes, regardless of denomination or imaged side. Finally, we briefly discuss the comparative benefits and limitations of our proposed technique and current methods.

To detect counterfeit notes in the denominations of ₹200, ₹500, and ₹2,000, we created a three-layer CNN model. Edge detection, picture segmentation and filtering, and pattern matching are all part of their suggested solution. a currency note identification system that works in real time. We also used OpenCV to do Brute Force picture classification and implemented it in Python, comparing it to CNN-based classification. CNN classification was shown to be more effective than Brute Force categorization.

Using Support Vector Machine algorithm. Using SVM algorithm to Extracting the features of the currency note. And finding currency note is real or fake.

FEATURES OF NOTE



The following characteristics are extracted and compared to the training dataset to determine if the dollar note is legitimate or fraudulent. Support vector machines (SVMs) are used to extract features [5,6]. We calculate the separation hyperplane when training an SVM such that the margin is maximized. We may interpret the SVM as a feature extractor since the hyperplane's coefficient vector is orthogonal to the hyperplane, and the training data of distinct classes projected onto the coefficient vector are maximally separated. In addition, we repeatedly find the projection vectors in the complementary space of the space encompassed by the already acquired projection vectors to yield more than one orthogonal projection vector.

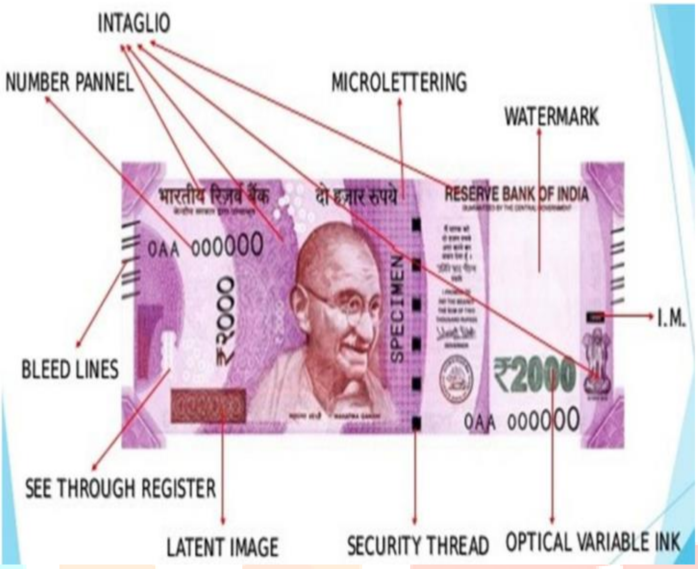
DISADVANTAGES:

- Used for only small datasets.
- Performance is not well.
- Requires high memory

Proposed System

Uses Convolutional Neural Network algorithm.

FEATURES OF NOTE AND EXTRACTION



Features of Note:

- Watermark, Security thread, Latent image, Bleed lines, See through register, Micro lettering, Optical variable ink, I.M., Number panel, Intaglio.
- Above features are extracted from the currency note by using computer vision. It is widely used to extract the features from an image.
- Those features are compared with the original collection of trained datasets.
- If the features of trained dataset and input image matched then it is a real note otherwise it is a fake note.

ADVANTAGES:

- Detect characteristics without the need for human intervention.
- Attempt to boost the system's speed.
- Aim to increase the accuracy of determining if a note is genuine or counterfeit.
- On huge data sets, it functioned admirably.

Methodology

1.Use the user's picture as input.

2.The RGB picture was captured and is presently being converted to grayscale.

3. Detection of edges in a grayscale picture as a whole.

4. The paper currency's properties will now be cropped and split.

5. The features of the currency note are retrieved after segmentation.

6. Each feature's intensity is computed.

7. If all of the conditions are met, the money note is considered genuine; otherwise, it is considered counterfeit.

This approach employs properties of currencies that are often utilised by ordinary people to distinguish between different banknote denominations. The following qualities can be used to verify the authenticity of a currency note:

The Safety Thread It's a 3mm windowed security thread with Hindi inscriptions and the RBI's banknote colour change. The thread colour changes from green to blue as the note is tilted.

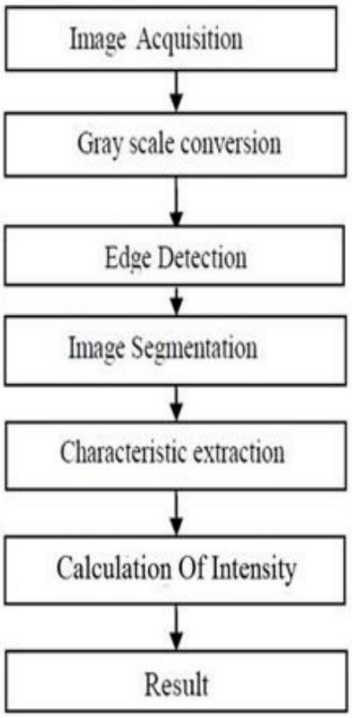
B. A serial number panel with banknote numbers ranging from tiny to big may be seen on the top left and bottom right sides.

C. Image that was obscured A vertical band on the front side of the denomination at right hand size. The currency contains a latent image of the denomination's number when held horizontally at eye level.

D. Watermarking When the card is held up to the light, it reveals a picture of Mahatma Gandhi, as well as multidirectional lines and a mark indicating the denominational numeral.

E. Mark of Appreciation Blind persons can recognise denominations with the use of a mark with intaglio print that can be touched. The denomination mark is five lines long, whereas the note line mark is seven lines long. In the same approach, other attributes were extracted.

WORK FLOW



1) Picture acquisition: The image is acquired using a basic digital camera and preserved under UV light.

2) Image preprocessing: It entails the procedures that must be followed before data analysis and information extraction may take place. Resizing images is done here.

3) Gray scale conversion and edge detection: The captured picture is RGB, which is now transformed to grey scale because it contains intensity information. The boundaries of grey scale pictures are discovered in this image after it has been further processed.

4) Image segmentation: Cropping is the process of separating a picture into several sections.

5) Feature extraction: Edge-based segmentation is now used to extract the features.

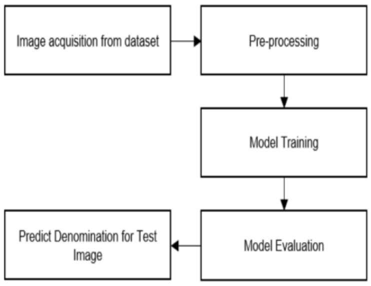
6) The intensity computation for each extracted feature has now been completed. If the computed intensity is more than 70%, the note is regarded genuine; otherwise, it is considered a forgery.

7) The ultimate conclusion is based on the intensity of all retrieved characteristics.

Process

Classification based on denomination

We utilised the dataset from [14], which contains 4002 pictures of Indian paper money notes in denominations of ₹10, ₹20, ₹50, ₹100, ₹200, ₹500 and ₹2000. The categorization procedure is outlined in the



stages below.

Pre-processing

• These photos were downsized and transformed into NumPy arrays of type 100x200x3, with the first two dimensions representing the image height and width, respectively, and the third dimension representing RGB pixel values.

• We've normalised the pixel values so that they're in the 0-1 range for the following stage in pre-processing.

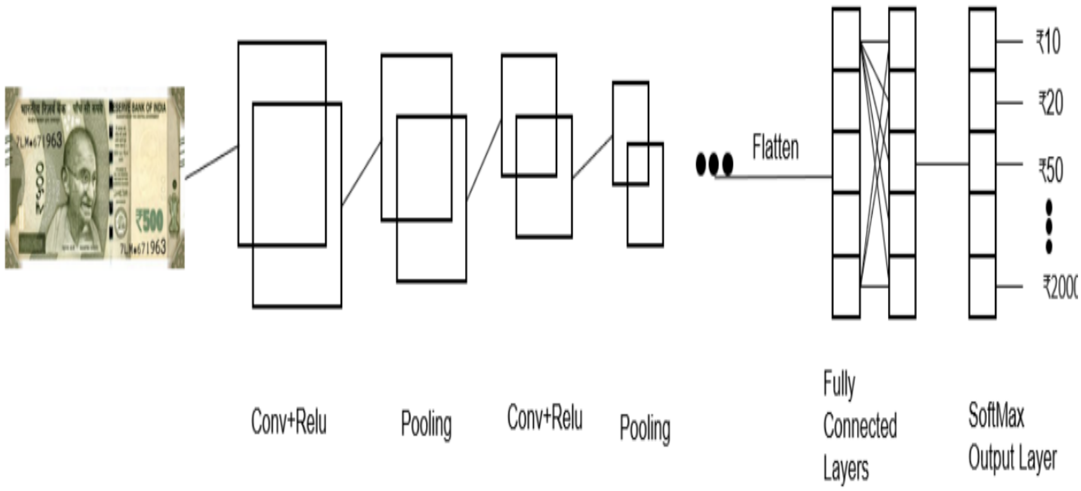
• We employed a three-layer CNN model with a Rectified Linear Unit (ReLu) activation function and two Max Pooling layers for model creation and training. The ReLu function retains the non-linearity of the pixels in the images, while the convolutional layers collect information from the images.

• The image's spatial dimension is gradually reduced by the pooling layers.

• Finally, on the output layer, SoftMax activation is utilised to allocate the denominations.

Model Testing

• Test image input is taken through the Jupyter File Upload system. The denomination with the highest probability predicted by the model is considered as the final output.



Counterfeit Verification

In the second phase of our proposed model, we have used Multi-scale Template Matching with OpenCV, implemented in Python.

Feature Extraction

• We start with a grayscale picture of an actual money note. The security characteristics are then retrieved using the bounding box Region of Interest (ROI) in OpenCV, which uses clever edge detection. Every denomination goes through the same procedure.

• An image's area of interest is a polygonal cross-section that comprises key characteristics. The ROI is frequently surrounded by a bounding box, which is an imaginary rectangle. Object detection is normally done with a bounding box and a region of interest.

Multiscale Template Matching

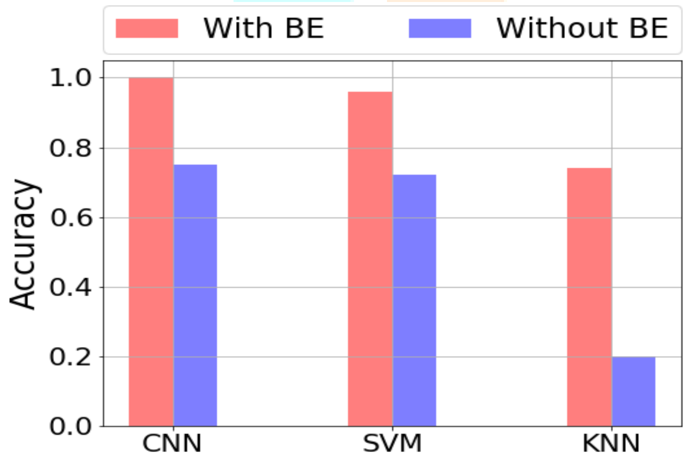
• Template matching is an image processing approach in which the existence of a template or a piece of an image is identified in another picture.

• Just as in 2-dimensional convolution, the template picture glides over the input image. Prior to template matching, a threshold value is determined. Under the template image area unit, the template and patch of the input picture are compared. The acquired result is compared to a set of criteria. The template is tagged as detected in the input image if the result exceeds the threshold.

• Multiscale template matching takes into consideration the fact that the source picture contains a scaled version of the template.

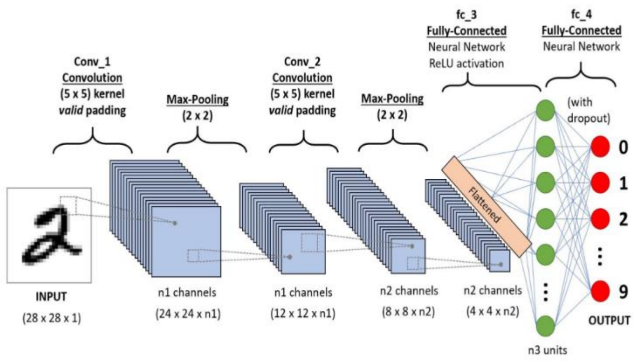
Counterfeit Prediction

• The security characteristics found on a real currency note are used as templates, and the test input picture is compared to these templates on a multiscale basis. The currency note is expected to be real if all of the security measures are present, and it is anticipated to be a fake if they are not.



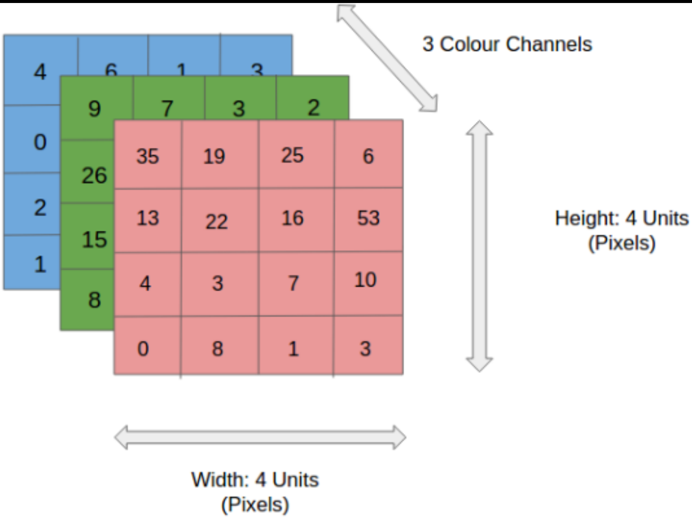
Background Elimination(BE)

CNN Architecture



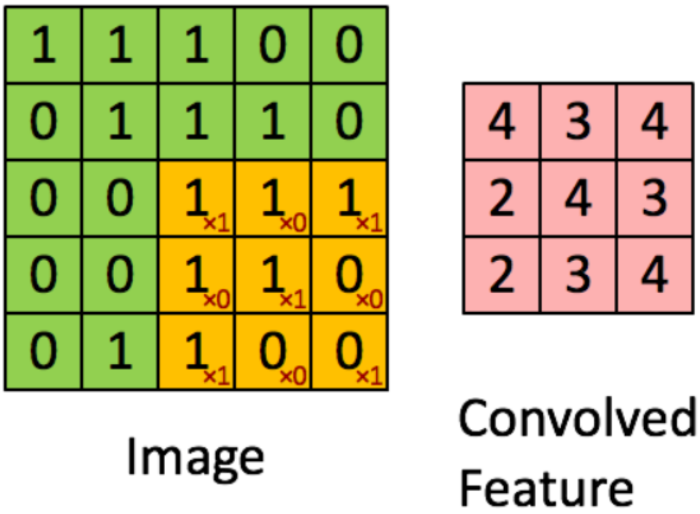
A **Convolutional Neural Network (ConvNet/CNN)** is a Deep Learning system that can take an input picture, assign relevance (learnable weights and biases) to various aspects/objects in the image, and distinguish between them. When compared to other classification methods, the amount of pre-processing required by a ConvNet is significantly less. While basic approaches need hand-engineering of filters, ConvNets can learn these filters/characteristics with enough training.

The design of a ConvNet is inspired by the organisation of the Visual Cortex and is akin to the connection pattern of Neurons in the Human Brain. Individual neurons can only respond to stimuli in a small area of the visual field called the Receptive Field. A collection of such fields overlap to cover the entire visual area.



We have an RGB picture with three colour planes — Red, Green, and Blue — that have been separated. Images can be stored in a variety of colour spaces, including Grayscale, RGB, HSV,

CMYK, and others



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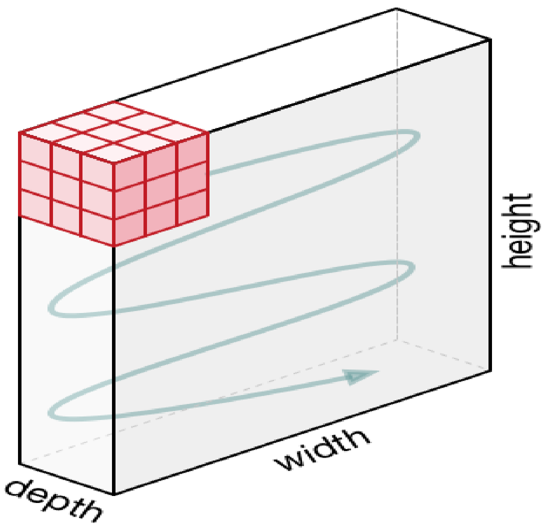
The green section resembles our **5x5x1 input image, I**. The element involved in carrying out the convolution operation in the first part of a Convolutional Layer is called the **Kernel/Filter, K**, represented in the color yellow. We have selected **K as a 3x3x1 matrix.**

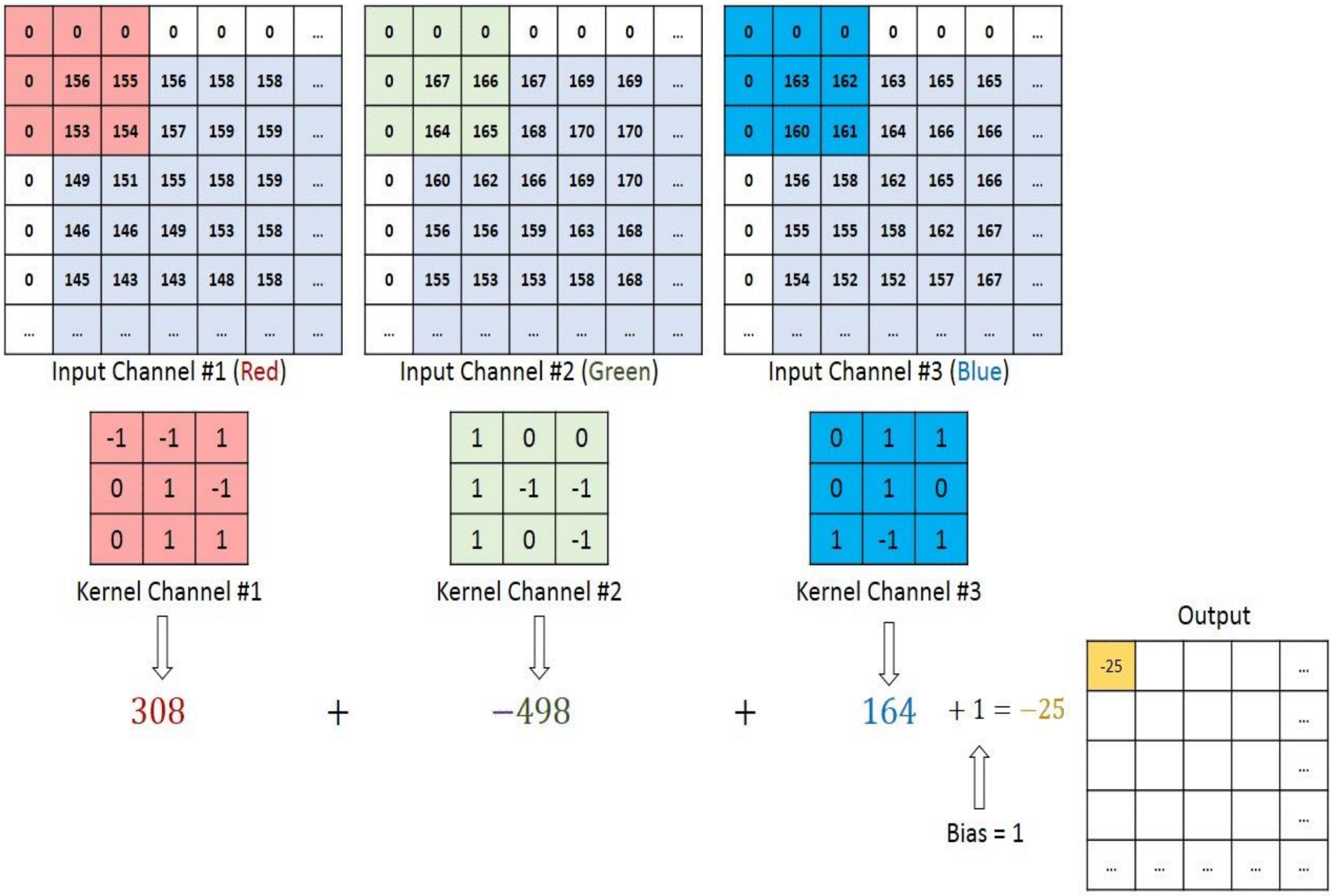
Kernel/Filter,

The Kernel shifts 9 times because of **Stride Length = 1 (Non-Strided)**, every time performing a **matrix multiplication operation between K and the portion P of the image** over which the kernel is hovering.



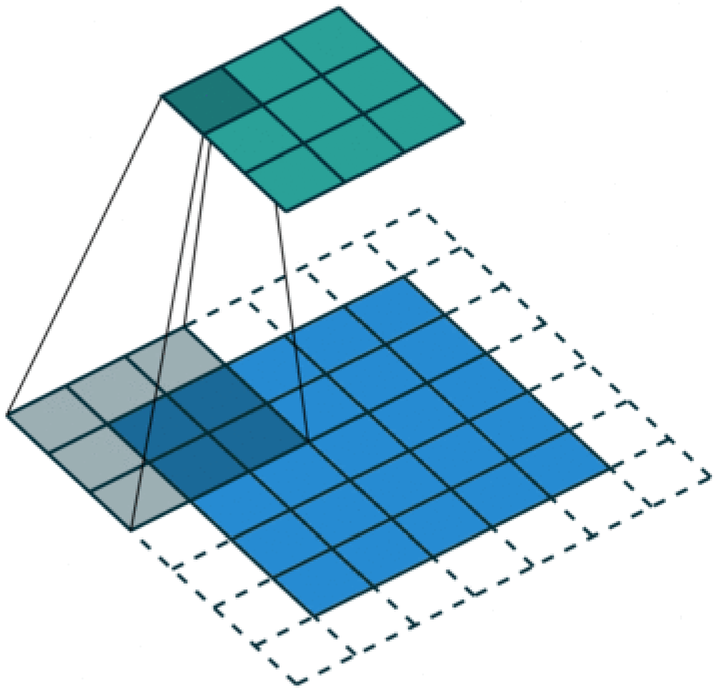
Movement of the Kernel

The filter moves to the right with a certain Stride Value till it parses the complete width. Moving on, it hops down to the beginning (left) of the image with the same Stride Value and repeats the process until the entire image is traversed.



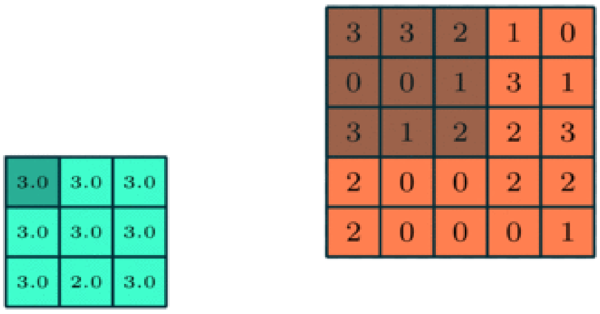
Convolution operation on a MxNx3 image matrix with a 3x3x3 Kernel

In the case of images with multiple channels (e.g. RGB), the Kernel has the same depth as that of the input image. Matrix Multiplication is performed between Kn and In stack ([K1, I1]; [K2, I2]; [K3, I3]) and all the results are summed with the bias to give us a squashed one-depth channel Convoluted Feature Output.



Convolution Operation with Stride Length = 2

POOLING LAYER

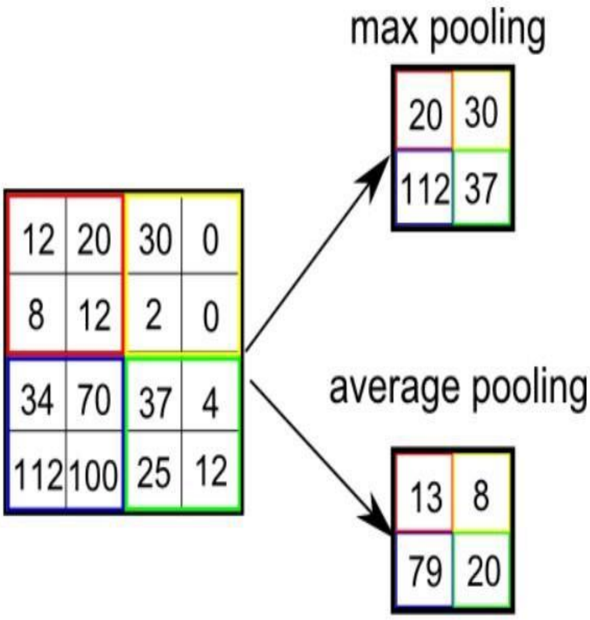


3x3 pooling over 5x5 convolved feature

The Pooling layer, like the Convolutional Layer, is responsible for shrinking the Convolved Feature's spatial size. Through dimensionality reduction, the computer power required to process the data is reduced. It's also beneficial for extracting rotational and positional invariant dominating features, which helps keep the model's training process running smoothly.

Pooling may be divided into two types: maximum pooling and average pooling. The largest value from the part of the picture covered by the Kernel is returned by Max Pooling. Average Pooling, on the other hand, returns the average of all the values from the Kernel's section of the picture.

Max Pooling also acts as a Noise Suppressant. It disables all noise activations as well as doing other tasks. Max Pooling works as a Noise Suppressant as well. It removes all noisy activations and conducts de-noising and dimensionality reduction at the same time. Average Pooling, on the other hand, just reduces dimensionality as a noise-suppressing strategy. As a result, we may state that **Max Pooling performs a lot better than Average Pooling**.

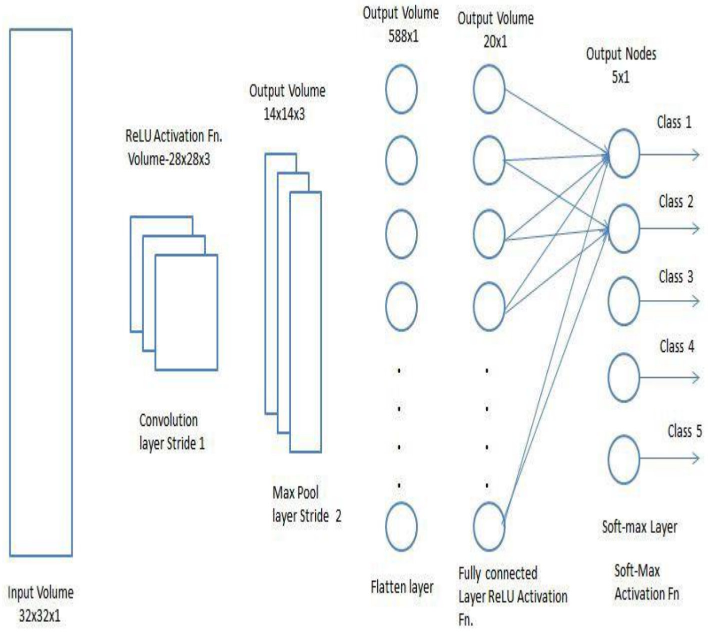


Types of Pooling

The i-th layer of a Convolutional Neural Network is made up of the Convolutional Layer and the Pooling Layer. Depending on the picture complexity, the number of such layers may be expanded even higher to capture even more low-level features, but at the cost of greater processing power.

We have successfully enabled the model to grasp the features after going through the aforesaid method. After that, we'll flatten the final result and input it to a standard Neural Network for categorization.

Classification — Fully Connected Layer (FC Layer)



Adding a Fully-Connected layer is a (typically) low-cost approach of learning non-linear combinations of high-level information represented by the convolutional layer's output. In such area, the Fully-Connected layer is learning a possibly non-linear function.

We'll flatten the image into a column vector now that we've turned it into a format suited for our Multi-Level Perceptron. Every round of training uses backpropagation to send the flattened output to a feed-forward neural network. The model can discriminate between dominant and certain low-level characteristics in pictures across a number of epochs and categorise them using the Softmax Classification approach.

Dataset Table:

Currency Dataset	Training(60%)	Testing(40%)	Total
5	6	4	10
10	11	7	18
20	13	8	21
50	15	10	25
100	16	11	27
200	18	12	30
500	22	14	36
2000	26	18	44

	Tp	Tn	Fp	Fn	Accurate %
5	-	4	-	-	100%
10	1	6	-	-	85%
20	-	8	-	-	100%
50	-	10	-	-	100%
100	-	11	-	-	100%
200	1	11	-	-	91%
500	1	13	-	-	92%
2000	0	18	-	-	100%

Accuracy Table:

Learning Method	Classification method	Computational Time(ms)
SVM	94.8%	82
Adaboost	93.6%	69
CNN	96%	23

CONCLUSION

This model was used to identify counterfeit cash. Because the monetary characteristics features are learnt layer by layer, the detection accuracy is quite high. We've looked at the entire currency picture so far, but in the future, we'll strive to include all of the money's security features by using appropriate structural design and training data. Furthermore, noise may be present in the taken image, which must be considered as part of the money recognition process's pre-processing. The recognition and detection of fake cash may also be improved by taking into account the patterns on the coin surface as characteristics.

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