Fake Currency Identification System Using Convolutional Neural Network

B. R. Shobha Rani, S. Bharathi, Piyush Kumar Pareek, and Dipeeka

Abstract Fake currency is a serious problem in India, and detecting it is crucial to maintain the integrity of the country's currency. There are various software programs available in India for detecting fake currency. These software programs use image processing techniques to analyze images of currency notes and identify any irregularities that indicate counterfeit notes. Existing methods for detecting counterfeit notes rely primarily on image processing techniques. A web-based detection system provides an easy-to-use interface for users to upload images of currency notes, send them to the CNN model (Venkata Raghu et al. in Int J Creat Res Thoughts (IJCRT) 10:2320–2882, 2004), and view the analysis results. Convolutional Neural Networks (CNNs) (Pallavi et al. in Int Res J Modernizat Eng Technol Sci 50:4076–4081, 2002) are used in the detection of counterfeit currency by analyzing the security features of currency notes and learning to differentiate between genuine and counterfeit notes based on those features. Using a real-time camera view (Selvi Rajendran and Anithaashri in IOP Conf Ser Mater Sci Eng 992:01201, 2020), this study will identify Indian banknotes by extracting features from notes, the model can identify counterfeit money. The model is trained with 80–20% training and test split, with each layer receiving the same learning rate of 0.001. After training the network for 200 cycles with 306 images, the training accuracy score 90.6%.

Keywords Deep learning · Convolutional neural network · Pre-processing

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1 Introduction

Fake currency detection refers to the process of identifying counterfeit or fake currency. Counterfeit currency is a fake imitation of genuine currency that is intended to deceive people into believing it is real. The detection of fake currency is essential to prevent its circulation and protect the economy from the adverse effects of counterfeiting. Fake currency detection involves the use of various techniques and technologies to determine the authenticity of banknotes and coins. These include visual inspection, ultraviolet (UV) detection, magnetic ink detection, watermark verification, microprinting, and other security features embedded in genuine currency.

Fake currency detection in India is a difficult task that necessitates a combination of technology, education, and training. It is critical to raise awareness of the security features of genuine notes and to provide small businesses with access to counterfeit detection machines.

Depending on the type of data and the complexity of the task, different machine learning algorithms [1] such as Naïve Bayes, Decision Tree Classifier, Random Forest, Support Vector Machines, KNN [2] can be used in fake currency detection. But the ability of deep learning algorithms to learn complex representations and automatically extract relevant features from the input data makes deep learning algorithms a powerful tool for fake currency detection, and can provide a more accurate and robust solution compared to traditional ML algorithms.

CNNs [3] can be used to analyze the various security features of genuine currency notes, such as watermarks, holograms, and microprinting. By training a CNN [4] on a large dataset of genuine and fake currency notes, the algorithm can learn to identify the features that are most indicative of a genuine note and distinguish them from fake notes. The use of CNNs for fake currency detection has several advantages over traditional methods. First, it can automate the detection process and reduce the dependence on human experts. Second, CNNs can learn to detect more subtle features than what is visible to the human eye, which can improve the accuracy of detection. Finally, CNNs can be trained on large datasets, which can help to improve their performance over time.

Using image processing techniques, extract the specific data from the currency image and apply the appropriate recognition strategy to determine the currency. The two primary ways to identify currency are by its geometric size and distinctive texture. The basic phases in an image processing approach include image acquisition, edge detection, grayscale conversion, feature extraction, image segmentation, and decision-making. The disadvantage of these techniques is that their detection efficiency is lower due to the difficulty of feature extraction.

2 Related Work

To determine whether a note is genuine or a forgery, the paper [3] employs the convolutional neural network method and image processing techniques. To execute data processing and data extraction, the Support Vector Machines algorithm with image processing was used, resulting in a less accurate result than the convolutional neural network. CNN improves performance by extracting all features of the currency, comparing them to existing datasets, and determining whether the currency is fake or genuine.

This paper [5] used MATLAB software to identify other countries' currencies and Indian counterfeit currency. For identification, they used banknotes, which are pieces of currency that differ in size, texture, and color. Model will then remove the highlights of certified notes by utilizing various parts of Digital Image handling, such as picture preparation, image segmentation, feature extraction, and viewing pictures.

Navya Krishna et al. [6] suggested utilizing CNN to identify fraudulent money notes. The Automatic Fake Currency Recognition System (AFCRS) is designed to recognize counterfeit paper money so that it can be determined whether it is genuine or not. The present fake currency problem brought on by demonetization affects the financial system and other fields. This research examines a different approach to convolution neural network that is considerably superior to earlier image processing techniques for identifying fraudulent note proof through their photographs.

It hinges on deep learning, which recently achieved remarkable success in image categorization. Through the use of an equivalent image, this approach can assist both humans and machines in gradually identifying counterfeit notes. The proposed system, can also be presented as a smartphone app that helps the general public tell the difference between authentic and genuine notes.

This paper [2] proposes a method for detecting fake currency using K-Nearest Neighbors, followed by image processing. KNN has a high accuracy for small data sets, making it suitable for computer vision tasks. The banknote authentication dataset was created using advanced computational and mathematical strategies to provide accurate data and information about the entities and features of currency. To obtain the final result at an accuracy of 99.9% after applying data processing and feature extraction are performed by implementing machine learning algorithms and image processing.

A vision-based system for banknote recognition using various machine learning and deep learning techniques is proposed by Sufri et al. [7]. They applied the DT, NB, KNN, SVM, and deep learning Alexnet algorithms and used the RGB values as features. Both SVM and BC outperformed KNN and DTC by obtaining 100% accuracy, whereas KNN and DTC both reached 99.7% accuracy.

According to Veerasetty et al. research [8], an effective novel-lightweight convolutional neural network (CNN) system for identifying Indian rupee notes has been developed for use in web and mobile apps. Furthermore, 4657 photos in total were captured to construct the dataset. All accepted currency notes, including the new 200, 500, and 2000-rupee notes as well as the old and new 10- and 20-rupee notes and 50- and 100-rupee notes, were utilized. Each shot is downsized to 1024 × 1024 pixels before being sent to the models as input.

Six supervised machine learning algorithms [1] are used in this paper to detect bank currency authentication using data from the UCI machine learning repository. To accomplish this, we used Support Vector Machine, Random Forest, Logistic Regression, Naive Bayes, Decision Tree, and K-Nearest Neighbor with three train test ratios of 80–20, 70–30, and 60–40 and measured their performance using quantitative analysis parameters such as precision, accuracy, recall, MCC, F1-score, and others. Furthermore, some SML algorithms provide 100% accuracy for a specific train test ratio.

This paper [9] proposes to create an automated system for Indian banknote recognition that is invariant of orientation and independent of the sides or faces of the notes using image processing and deep learning techniques. Currency note images are pre-processed to compensate for rotation before being passed through a technique to determine whether they are Indian banknotes or not. If an Indian banknote is discovered, the denomination is classified in two ways: (i) extracting color and texture features to form feature vectors, which are then used to classify test samples using KNN; (ii) images of Indian banknotes are directly fed into a convolutional neural network (CNN) [7] for classification.

The proposed framework [10] begins with the capture of still images. To extricate the ROI and encourage the layout coordinating method, basic image handling strategies such as thresholding, noise evacuation, histogram equalization, and division are used. The Matlab framework takes into account offline captured images, whereas the Android framework was designed to coordinate visually impaired clients. Indian currency papers have used Alexnet, Googlenet model, and Vgg16 for training and testing to tune the network models. Vgg16 confirmed an excellent performance when compared to Alexnet and Googlenet with 95% accuracy.

3 Methodology

CNNs [4] can be implemented for fake currency detection using a combination of several techniques, including data pre-processing, model architecture design, and model training and evaluation.

a. Dataset preparation: A dataset of banknote images is collected, which includes both genuine and counterfeit banknotes. A dataset of real and fake banknote images is collected, then compared to identify which images are real and which are fake.
b. Data pre-processing: The images in the dataset have been pre-processed to adjust for lighting and eliminate any background noise or artifacts. This may entail scaling the images to a specific size, making them grayscale, and adjusting the pixel values.

c. Model architecture design: A CNN architecture is designed to effectively extract features from the input images and classify them into genuine or counterfeit banknotes. This can involve designing the layers and filters of the CNN and selecting appropriate activation functions, such as ReLU or sigmoid.
d. Model training: To reduce the discrepancy between the predicted labels and the actual labels of the images, the CNN is trained on the dataset using an optimizer. In order to increase the CNN's accuracy on the validation set, it is necessary to divide the dataset into training and validation sets and modify the CNN's parameters. The CNN was trained using Adam optimizer.
e. Model evaluation: Once the CNN has been trained, it is evaluated using a test dataset that is separate from the training and validation datasets. The evaluation metrics can include accuracy, precision, recall, and F1-score. When CNN performs well on the test dataset, then its deployed for real-time detection of counterfeit banknotes.

4 Implementation

A web-based framework is designed that accepts the image and passed to CNN model which analyze and detect if the currency image is real or fake currency by the system by displaying status as real or fake on the web browser. A web application is designed and developed using python and Flask.

This system suggests a multimodal classes risk prediction model with limited notes that is more accurate and is based on convolutional neural networks. With accurate stage forecasts, we will be able to diagnose real from fraudulent with more accuracy.

4.1 Data Collection

A real-time database of legitimate and counterfeit money is created. The evaluation considers notes of 10, 20, 50, 100, 200, 500, and 2000. The images were taken with a 12-megapixel phone camera in a variety of lighting conditions and from various angles. The new currency notes are collected for analysis, while the counterfeit bank notes are collected. The data is divided into training and test datasets. This paper's architecture makes use of 80% training data and 20% test data.

4.2 Pre-processing

The following are different pre-processing techniques used on dataset before passing them to the model as shown in Fig. 1.

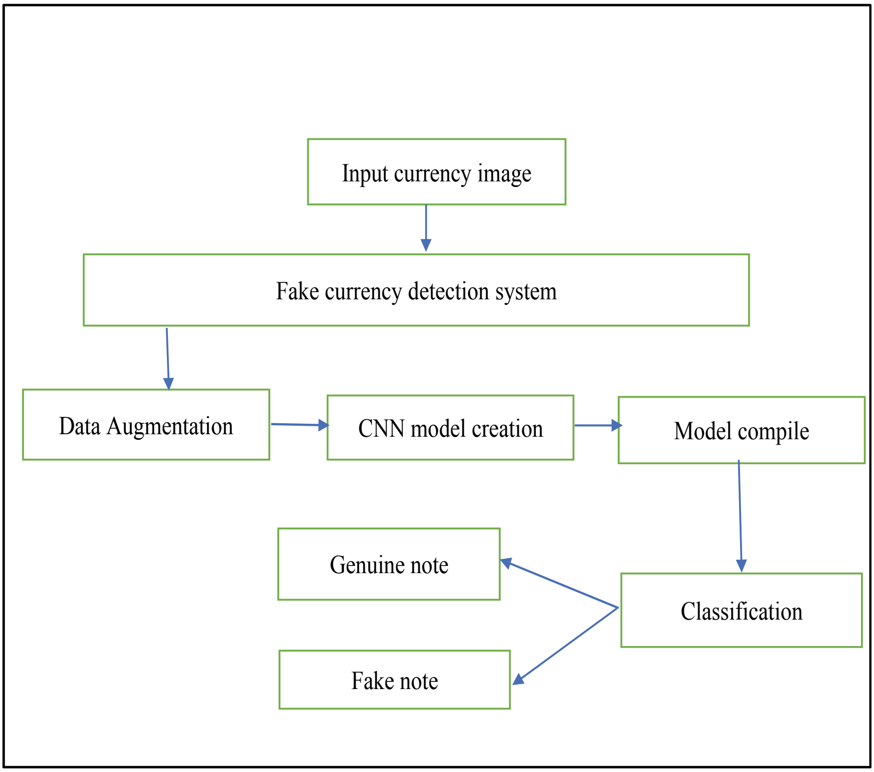

Fig. 1 Proposed architecture

Image resizing: The images of the banknotes may vary in size, which can affect the CNN's performance. As a result, to ensure consistency across the dataset, the images may be resized to a fixed size.

Image normalization: The pixel values in the images may vary, making it difficult for the CNN to learn the patterns in the images. As a result, the pixel values are normalized to a fixed range, such as [0, 1], to improve the CNN's performance.

Image cropping: Banknote images contain unnecessary background or artifacts, which can degrade CNN performance. As a result, the images are cropped to remove any distracting elements and focus on the banknote itself.

Image rotation: The banknotes in the images are oriented in different directions, that affects the CNN's performance and same orientation is retained throughout the dataset.

Image augmentation: To increase the size of the dataset and improve the robustness of the CNN, the dataset is augmented with variations of the original images, such as rotations, translations, and scaling.

5 Model Training

The currency detection model developed using the deep learning method can be applied to a wide range of banking and money-exchange applications and deployed as a single application. This section contains the results of image processing operations. A Python web framework is used to create dependable web apps for website frameworks such as Python and Flask.

In the system, process of fake currency detection is analyzed as follows:

A GUI is designed with three buttons on the webpage. A start button is used to begin the acquisition process, the clear button to erase prior data, and the exit button to log out of the program.

- Step 1: The camera is used to acquire images, which are then sent to the processing unit.
- Step 2: A web page for this system contains a graphical user interface (GUI) that can be accessed for the identification of counterfeit currency using either a PC or a smartphone.
- The system's real-time video stream enables users to capture the image of the currency note by positioning it in front of the camera and taking a picture, which is then saved in a file on the computer or laptop where the system is installed.
- Step 3: Next, choose the control button for the appropriate denomination from GUI to check for detection of the currency note and then passed for segmentation.
- Step 4: The segmented image is cropped and scaled which is compared with the images that are stored in the database.
- Step 5: The outcome is then shown in the result panel of the webpage. The user can examine whether the currency note is real or fake, as well as the accuracy of the forecast, after uploading the image and selecting the analyze image button.
- With the help of the TensorFlow and Keras libraries, this system primarily focuses on the deep learning element of image categorization that is used to identify currencies.

5.1 Training Using CNN

Fake currency detection using CNN architecture [11] involves designing a model that can effectively extract features as shown in Fig. 2 from the input images and classify them into genuine or counterfeit banknotes.

Fake currency detection using CNN architecture typically involves the following steps:

i. Input layer: The input layer of the CNN takes in the pre-processed images of the banknotes. The size of the input layer is determined by the size of the pre-processed images.
ii. Convolutional layers: The convolutional layers of the CNN extract feature from the input images by applying a set of filters to the images. Each filter is a

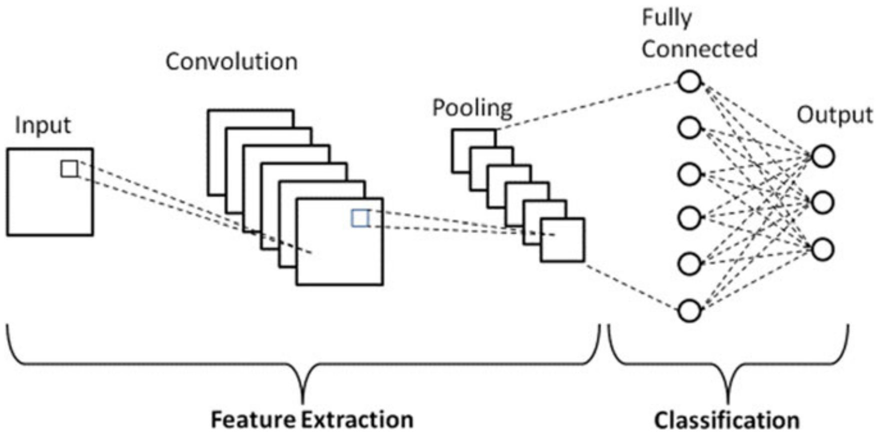

Fig. 2 Convolutional neural network architecture

small matrix that slides over the image and performs a dot product operation, producing a feature map that highlights the presence of certain patterns or edges in the image. The number of filters and their size can be adjusted based on the complexity of the task.

iii. The Rectified Linear Unit (ReLU) layer introduces non-linearity into the network by applying a non-linear activation function to the feature maps.

iv. Pooling layers: The pooling layers of the CNN reduce the spatial size of the feature maps by summarizing the information in each neighborhood of the map. This can help to reduce the dimensionality of the data and make the CNN more computationally efficient.

v. Dropout Layer: The dropout layer randomly drops out some of the nodes in the network during training to prevent overfitting.

vi. Fully connected layers: The fully connected layers of the CNN perform the classification task by taking the flattened output of the pooling layers and applying a set of weights and biases to produce a probability distribution over the classes. The number of nodes in the fully connected layers and the number of output classes can be adjusted based on the task.

vii. Output layer: The output layer of the CNN produces the final output of the classification task, which is a probability distribution over the classes. The class with the highest probability is selected as the predicted class.

The structure of CNN includes convolutional, pooling, Rectified Linear Unit (ReLU), and fully connected layers as shown in the Fig. 2.

The CNN architecture implemented for fake currency detection takes padding and stride as value 1 and is given kernel value with 3×3 along with Rectilinear Unit (ReLU) activation function as shown in Fig. 3 above. The input given as currency note image takes channel with a dimension of 1 and passed to next layer with a channel size of 32 for extracting 32 feature maps. Further, a ReLU activation function is

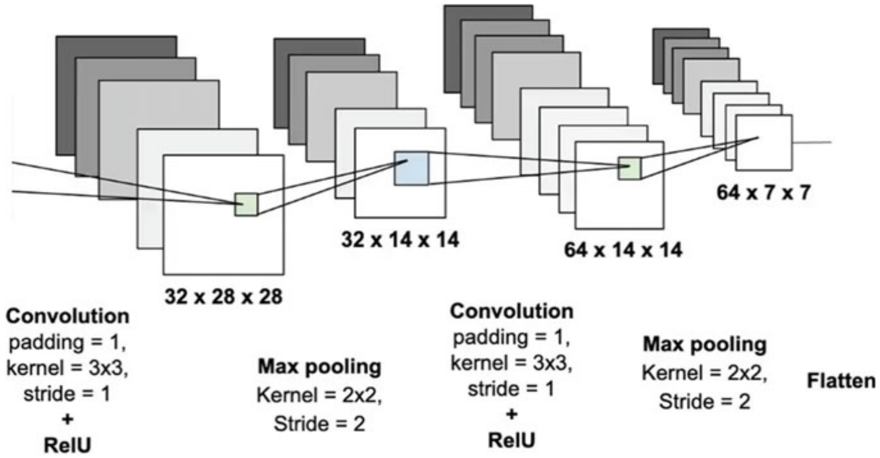

Fig. 3 Convolutional neural network architecture with kernel, padding, and stride values

applied to give the next layer with a kernel of 2 × 2 and stride 2 to get 14 feature maps by down scaling. This process is repeated until the analysis reaches 128 feature maps to form fully connected layer with softmax a s activation function and using ADAM optimizer with a learning rate of 0.001 resulting in 96.6% accuracy and 80% success rate.

6 Result and Discussion

The model is trained on NVIDIA GPU GeForce series with a minimum of 4 GB of VRAM is recommended for running CNN models. The CNN is trained with CUDA version 10 with cuDNN library compatible with version 7.4.5 on an Ubuntu 18.04 bionic sever. For the initial training, the entire training dataset was used, with each layer receiving the same learning rate of 0.001. The network is trained for 200 epochs with 306 images before being retrained for 300 epochs to increase the training accuracy score from 84.4 to 96.9%. The model has a success rate of 80% in distinguishing genuine Indian rupee notes from counterfeit ones. In two of ten cases, the proposed model failed to correctly identify two original currency notes with more stains. This application's success rate can be increased by increasing the data set size and adding more images that were recorded.

After the program is complied, the screen showed in the Fig. 4 will display. It displays a new window contains click below to choose picture for testing. Then we should click on the "get photo" option on the screen. The testing data content page will open, in that select the image or picture you want to test (Fig. 5).

After selecting the image, the selected image will be visible on the window. It shows the option to analyze the image as "Analyze image". Click on the image.

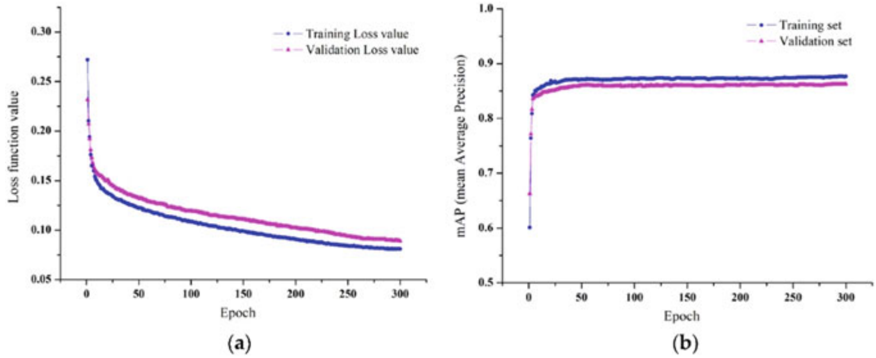

Fig. 4 Training and validation loss at 300 epochs

Fig. 5. Choosing the picture for testing

After analyzing the image which we selected it shows the image is real or fake. In the above Fig. 6 it shows the image is real (Figs. 7, 8).

Fig. 6 Testing a picture to analyze the image

Fig. 7 After analyzing it shows the image is real

Fig. 8 A different image to analyze then after analyzing, shows the image is fake

7 Conclusion

A web-based framework [10] provides a user-friendly interface for users to upload images of currency notes, pass them to the CNN [7] model and view the results of the analysis. This interface can be designed to be intuitive and easy to use, even for non-technical users. A convolutional neural network is trained to detect fake currency in real time by capturing the currency notes through camera. The suggested model is expected to function flawlessly for Indian currency in denominations of Rs. 10, 20, 50, 100, 500, and 2000 and can be applied to quickly detect a number of cash note's attributes. In this paper, 306 images were used, of which 80% are used for training and the remaining 20% are used for validation. The model's learning rate was set to 0.001, and it eventually turned in results with an accuracy of 96.6 and an overall success rate of 80%. Web-based frameworks provides visualizations of the results of the analysis, such as heatmaps, histograms, or other graphical representations of the CNN model's output as future enhancement. This would be easier for users to interpret the results of the analysis and make decisions based on them which improve the accuracy and effectiveness of the analysis.

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