



# IJRASET

International Journal For Research in  
Applied Science and Engineering Technology



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# INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

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**Volume:** 11    **Issue:** IV    **Month of publication:** April 2023

**DOI:** <https://doi.org/10.22214/ijraset.2023.51314>

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# Detection of Fake Currency using Machine Learning

Pushpa R N<sup>1</sup>, Aditya Aithal H K<sup>2</sup>, Ganesh Prasad M<sup>3</sup>, Manoj R Divakar<sup>4</sup>, Hithesha H G<sup>5</sup>

<sup>1, 2, 3, 4, 5</sup>Department of Computer Science and Engineering, Jawaharlal Nehru New College of Engineering, Shimoga, India

**Abstract:** *The problem of detecting fake currency notes is crucial for maintaining the integrity of the economy. In recent years, there has been a surge in the use of deep learning models for detecting counterfeit currency using image processing. For Human being it is very difficult to identify fake currencies, So automatic systems for detection of fake currency is important. In this project, we propose a Convolutional Neural Network (CNN) model for detecting fake currency notes. To train our model, we use a dataset of images containing both genuine and fake currency notes of different denominations. The dataset is pre-processed by resizing all images to a fixed size and normalizing the pixel values. The pre-processed images are then split into training and validation sets for training and testing the model, respectively. This project is modelled as a CNN for automatic feature extraction and classification. The Experimental results validate that the proposed model effectively recognises a real and counterfeit currencies of various denominations with the confidence score.*

**Keywords:** *Machine Learning, Image processing, Convolutional Neural Network*

## I. INTRODUCTION

Counterfeit currency is a major problem worldwide, with counterfeiters constantly improving their techniques and making it more challenging to identify fake notes. The use of machine learning and image processing techniques can help in developing an automated system for fake currency detection. Image processing involves analysing and manipulating images to extract useful information, such as features that can be used to distinguish between real and fake currency notes. Convolutional Neural Networks (CNNs) have shown great success in image recognition tasks, making them a suitable tool for detecting counterfeit currency. The process of fake currency detection using CNNs involves three major stages: dataset collection, training, and testing. The dataset collection stage involves collecting a large number of genuine and fake currency images. The dataset should be diverse and representative of the currency types in circulation. The collected dataset then undergoes pre-processing to remove any noise or distortion that may interfere with the CNN's analysis. The training stage involves feeding the pre-processed dataset to the CNN using supervised learning techniques. During this stage, the CNN learns to recognize patterns and features that distinguish genuine and fake currency. The training process may take some time, and the accuracy of the CNN improves with more data and iterations. The testing stage involves feeding new currency images to the trained CNN. The CNN then analyses the features of the input image and determines whether it is genuine or fake. Once the CNN model has been trained, it can be used to detect fake currency notes in real-time. The CNN's output is further analysed using machine learning algorithms to improve its accuracy and reliability. Overall, the use of CNNs for fake currency detection can provide a fast, accurate, and automated solution to the problem of counterfeit currency. This can help in reducing financial fraud and ensuring the integrity of financial systems. The technique can be extended to other areas, such as document verification and fraud detection, where image processing and machine learning can be applied to improve accuracy and efficiency.

## II. LITERATURE SURVEY

[1] Aman Bhatia, Vansh Kedia, Anshul Shroff, Mayand Kumar, Bickey Kumar Shah, Aryan, The paper proposes a method for detecting fake currency using machine learning algorithms and image processing techniques. The approach involves analyzing various features of currency notes, such as texture, watermark, and serial number, to distinguish between real and counterfeit notes. The proposed method achieved a high accuracy rate in detecting fake currency. [2] Megha Jadhav, Yogesh kumar Sharma, G. M. Bhandari, The paper proposes a system that uses deep learning techniques, specifically convolutional neural networks, for automatic detection of forged banknotes and identification of the currency denomination from images captured under varying lighting conditions. The proposed system achieved high accuracy in currency identification and forged banknote detection. [3] Asfaw Shefraw Alene, Dr, Million Meshesha, The paper proposes an optimal feature extraction technique for the recognition of Ethiopian

paper currency using machine learning. The proposed system achieved high accuracy in recognizing different denominations of Ethiopian currency notes. [4] Veling, Miss. Janhavi P. Sawal, Miss. Siddhi A. Bandekar, Mr. Tejas C. Patil, Mr. Aniket L. Sawant, The paper proposes a method for recognizing fake Indian currency using image processing techniques and machine learning algorithms in MATLAB. The proposed system analyzes various features of the currency note and classifies it as genuine or fake with high accuracy. [5] Kiran Kamble, Anuthi Bhansali, Pranali Satalgaonkar, Shruti Alagundgi, The paper presents a method for detecting counterfeit currency using a deep convolutional neural network. The approach involves training the network on a dataset of real and counterfeit currency images and using it to classify new images as real or fake with high accuracy. The proposed method shows promising results in detecting counterfeit currency. [6] G.Hariharan , D.Elangovan, The paper proposes a method for recognizing and eradicating proxy notes using image processing techniques and deep learning. The process involves image acquisition, pre-processing, segmentation, and deep learning using a CNN algorithm. The method utilizes anisotropic diffusion filters, adaptive coherence mean improvement, and adaptive region growing segmentation to enhance the quality of images and extract image characteristics. The limitations include high time consumption for better accuracy using the CNN algorithm. The proposed method has the potential to improve transparency and accountability in the electoral process. [7] Vanajakshi, Veena, Yadhunandan, Sowjanya.U, Anitha, The paper proposes a system for detecting counterfeit Indian currency notes using image processing techniques. The system involves pre-processing the input image, segmenting the note region, extracting features, and using a classifier to determine whether the note is genuine or counterfeit.

### III.METHODOLOGY

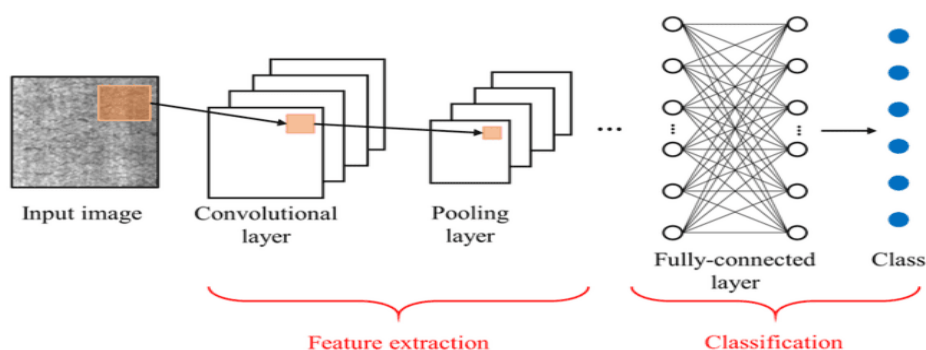


Fig. 1 Architecture of proposed method

The architecture of a proposed method for image processing, specifically for binary classification tasks. It consists of multiple layers of Convolutional Neural Networks (CNNs) followed by activation functions, max pooling layers, and fully connected layers. The first layer is a Conv2D layer with 32 filters of size (2, 2) and the input shape of the images is specified as input\_shape. The activation function used after this layer is ReLU, which helps in introducing non-linearity into the model. The next layer is a MaxPooling2D layer with pool size (2, 2) which reduces the dimensionality of the feature maps and helps in avoiding overfitting. The same pattern is repeated for the next two layers, with 32 filters of size (2, 2) and 64 filters of size (2, 2), respectively. After each Conv2D layer, an activation function and a MaxPooling2D layer are added. The final layer of the model is a dense layer with 64 units followed by an activation function. A dropout layer is added to prevent overfitting, with a dropout rate of 0.5. The final dense layer consists of a single unit with a sigmoid activation function, which produces the binary classification output. Overall, this architecture consists of a combination of convolutional and fully connected layers, which is a common approach in designing CNN models for image processing tasks.

### IV.SYSTEM DESIGN AND IMPLEMENTATION

#### A. Data Collection

Dataset collection is a crucial step in image processing projects, as the performance and accuracy of the final model heavily rely on the quality and quantity of the dataset used for training and testing. Collecting a diverse and comprehensive dataset helps in building a robust and generalizable model that can accurately detect or classify different types of images in real-world scenarios. Moreover, the quality of the dataset is equally important as the quantity. The dataset should contain high-quality images with consistent lighting, resolution, and colour balance, to ensure that the model can learn meaningful features and patterns from the images.

Additionally, it is essential to ensure that the dataset is balanced, with an equal number of images for each class to avoid bias and overfitting. The importance of dataset collection in image processing projects cannot be overstated, as it forms the foundation for building accurate and robust models that can perform well in real-world scenarios.

### B. Data pre-processing

The data pre-processing is performed using Keras ImageDataGenerator class, which applies various transformations to the images to increase the variety of the training data and prevent overfitting.

The pre-processing steps applied are:

- 1) *Rescaling*: The images are rescaled by dividing each pixel value by 255. This step normalizes the pixel values to the range [0,1].
- 2) *Shear range*: The shear range parameter randomly applies a shear transformation to the images. This transformation slides one part of the image in a certain direction, creating a diagonal motion blur effect.
- 3) *Zoom range*: The zoom range parameter applies a random zoom to the images. This transformation can help the model detect patterns at different scales.
- 4) *Horizontal flip*: The horizontal flip parameter randomly flips the images horizontally. This transformation helps the model learn rotation-invariant features.

### C. Feature extraction

Feature extraction is performed using Convolutional Neural Network (CNN). CNN is a popular deep learning technique for image classification tasks, which involves the extraction of relevant features from input images. The input image size is defined, and the location of the training and testing data directories is specified. Then, the number of training and validation samples, number of epochs, and batch size are defined. Next, the input shape of the CNN is defined based on the image data format, either with 3 colour channels or with 3 channels first. A Sequential model is defined with multiple convolutional layers, max pooling layers, and a dense layer with a sigmoid activation function for binary classification. The model is compiled with the binary cross-entropy loss function, the RMSprop optimizer, and accuracy as the evaluation metric. The next step is data augmentation, which is done using ImageDataGenerator. The data is rescaled by 1/255 to normalize it and prevent overfitting. Shear range, zoom range, and horizontal flip are applied to the training data to augment the dataset, while only rescaling is applied to the validation data. The train and validation generators are created using flow\_from\_directory, where the target size, batch size, and class mode are defined. Finally, the model is trained using the fit\_generator method with the train and validation generators. The trained model is saved to the 'model\_saved.h5' file.

### D. Image Classification

The pre-trained deep learning model is used to perform image classification on a single image. The model was trained on a large dataset of labelled images and is now being used to predict the class label of a new input image. It loads a pre-trained Keras model, which is a deep learning framework built on top of TensorFlow. It also loads a file containing the class labels, which maps the numeric output of the model to a human-readable label. The input image is then pre-processed by resizing it to 224x224 pixels and normalizing its pixel values. This step ensures that the input image has the same format as the images used to train the model. The pre-processed image is then fed into the pre-trained model to make a prediction. The model predicts the class probabilities of the image belonging to each of the possible classes. The class with the highest probability is chosen as the predicted class label of the input image. Finally, the predicted class label and its corresponding confidence score are printed. This information can be used to determine how confident the model is in its prediction.

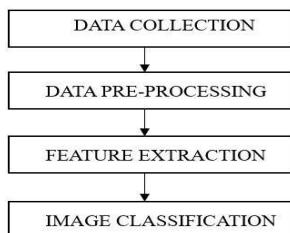


Fig. 2 Framework of proposed system

**E. Real time currency detection**

The process of detecting fake currency in live video using CNN for "Fake currency detection using image processing" is similar to the process of detecting fake currency in a single image. However, there are some additional challenges that need to be considered when working with live video. These challenges include handling the video input stream, processing multiple frames per second, and ensuring the detection process is accurate and fast enough to work in real-time. One approach to addressing these challenges is to use a pre-trained CNN model for image classification and object detection. This pre-trained model can be fine-tuned on a dataset of real and fake currency images to adapt it to the specific task of detecting fake currency in live video. The live video feed can be captured using a camera or other video input device and processed frame-by-frame by the CNN model. The output of the CNN model can be displayed in real-time, indicating whether the currency in the current frame is real or fake. To optimize the performance of the CNN model for live video processing, several techniques can be used, such as reducing the input image size, applying image pre-processing techniques, and optimizing the CNN architecture and hyperparameters. Additionally, multi-threading and parallel processing techniques can be used to speed up the processing of multiple video frames in real-time. Overall, the process of live real or fake currency detection using CNN for "Fake currency detection using image processing" involves capturing the video input stream, processing each frame using a pre-trained CNN model fine-tuned on real and fake currency images, and displaying the output in real-time.

**V. RESULT**

In order to test the efficiency of the system one can collect additional images of currencies in the dataset and see if the system recognizes them. But to have significant results another set of suitable test images would have to be found. And also, accuracy graph obtained from our experimental setup.

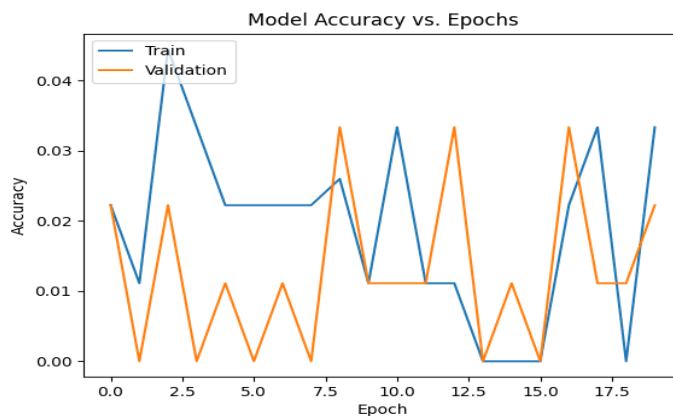


Fig. 3 Accuracy rate graph obtained from the experimental setup



Fig. 4 Main Page of the project



Fig. 5 Uploading the specific image from the test database



Fig. 6 Main screen content after uploading the currency image



Fig. 7 Classification of the image as fake currency



Fig. 8 Classifying the image as real currency

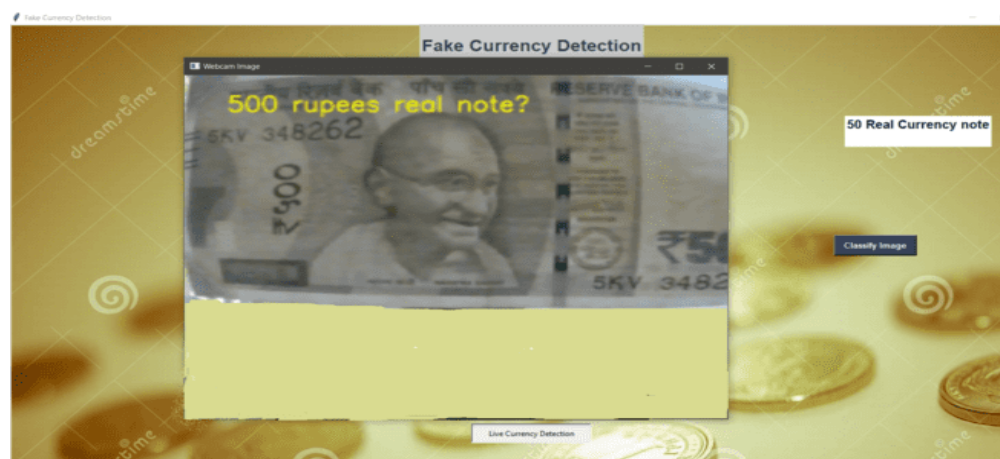


Fig. 9 Detection of the currency in real time using webcam

## VI. CONCLUSION

The project "Fake currency detection using machine learning" provides an in-depth analysis of the proposed approach for detecting counterfeit notes. The report details the methodology used for data collection, pre-processing, and feature extraction. It also provides a comprehensive overview of CNN architecture and implementation and its model's performance. The project's results demonstrate that the use of CNNs in fake currency detection can be highly effective in accurately identifying counterfeit notes. The CNN model trained on the dataset achieved high accuracy, demonstrating its potential as a reliable tool for detecting fake currency. Project emphasizes its potential to prevent financial losses and illegal activities related to counterfeit notes. The proposed approach can be highly beneficial for banks, businesses, and individuals in detecting fake currency, preventing further distribution, and ensuring financial security and also provides valuable insights into the development of a robust and effective system for detecting counterfeit notes. The use of CNNs in fake currency detection can significantly improve the accuracy and reliability of the system, making it an essential tool for financial institutions and businesses. Overall, the outcomes can pave the way for further research and development in this area, ultimately leading to improved financial security and stability.

## VII. ACKNOWLEDGMENT

We express our sincere gratitude to our guide, Mrs. Pushpa R.N for his suggestions and support during every stage of this work. We also convey our deep sense of gratitude to Dr. Poornima K M, Head of the department. we would like to express our sincere gratitude to all those who have contributed to this paper submission to IJRASET. we would like to thank co-authors for their valuable insights and contributions to this work. we would also like to extend our appreciation to the reviewers and editors for their time and effort in reviewing and improving this manuscript. Finally, we are grateful to my institution for providing me with the necessary resources to carry out this research.



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