

FAKE CURRENCY DETECTION USING CONVOLUTION NEURAL NETWORK

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ABSTRACT

Counterfeit currency paper notes pose a significant threat to the economy of a country, as they are produced without the legal sanction of the state. It is imperative to detect and distinguish between real and fake currency notes to prevent the proliferation of such notes in circulation. However, it is often challenging for an ordinary person to identify counterfeit notes. While banks and other financial institutions have sophisticated systems to detect fake notes, there is no such system readily available to the public. In this research paper, we propose a system that utilises deep learning algorithms, specifically Convolutional Neural Networks (CNNs), to accurately classify between real and fake currency paper notes. The system can operate in real-time, processing a picture of the paper note to determine its authenticity. We evaluate the performance of the proposed system using a dataset of real and counterfeit currency notes and achieve high accuracy in detecting fake notes. Our proposed system can be useful in various settings, including banks, financial institutions, and businesses that handle cash transactions. By detecting counterfeit currency notes promptly, we can prevent their circulation, thereby safeguarding the economy and the public from financial losses.

Keywords: Counterfeit, Real, Convolution Neural Network, Deep Learning, Classification.

I. INTRODUCTION

Counterfeit currency notes continue to be a pressing issue for governments and financial institutions worldwide. Criminals produce counterfeit notes to deceive unsuspecting individuals and businesses, leading to significant economic damage. To combat this problem, several technical advancements have been proposed to detect counterfeit currency notes. However, these solutions have limitations that need to be addressed to ensure their effectiveness. The proliferation of counterfeit currency notes can cause significant damage to the financial stability and security of a nation. Moreover, it is often challenging for an ordinary person to distinguish between real and fake currency notes. Hence, detecting counterfeit currency notes has become a crucial task for financial institutions and law enforcement agencies. To overcome these limitations, we propose a new model that uses Convolutional Neural Networks (CNNs), a type of Deep Learning algorithm, to distinguish between fake and real currency notes. The proposed system requires a large dataset of both real and counterfeit currency notes to train the CNN model effectively. Once the model is trained, it can be integrated into a user interface that enables users to determine the authenticity of currency notes.

The remainder of the paper is organised as follows : Section II (Related Work) will review and discuss previous studies and literature on the research topic, highlighting gaps in the existing literature. Section III (Dataset) will describe the dataset used in the study. Section IV (Proposed System) will present the proposed system for addressing the research problem. Section V (CNN Model) will detail the convolutional neural network (CNN) architecture used in the study. Section VI (Experimental Results) will report and analyse the results of the experiments conducted. Section VII (Conclusion) will summarise the findings of the study and discuss their implications. Finally, Section VIII (References) will list the sources cited in the paper.

II. RELATED WORK

Numerous studies have been conducted to detect and identify counterfeit currency notes using different techniques, including machine learning and image processing.

[1] Kiran Kamble, Anuthi Bhansali, Pranali Satalgaonkar, and Shruti Alagundgi proposed a model using a custom convolution neural network that was only trained with a dataset including the 500 and 2000 currency

notes. However, no other currency notes were included during the training, and the model was proposed immediately after demonetisation. The accuracy of this model was only 85.6%, indicating a need to improve the model and include all types of currency notes in the dataset.

[2] Aman Bhatia, Vansh Kedia, Bickey Kumar Shah, Mayand Kumar, and Anshul Shroff proposed a comparative study of K-Nearest Neighbours (KNN), Support Vector Classifier (SVC), and Gradient Boosting Classifier (GBC). This work provided an in-depth comparison of these models instead of focusing on a single model.

[3] Ms. Megha Jadhav, Dr. Yogesh Kumar Sharma, and Dr. G.M. Bhandari proposed a model using Deep Learning and a dataset of various country currency notes, not just Indian currency. However, there is a need to propose a model for identifying fake Indian currency notes specifically.

[4] R. Sumalatha, B. Jayanth Reddy, and T. Venkat Ram Reddy proposed a model using predefined convolutional networks. They conducted a comparison study between various predefined CNN models like Darknet53, Alexnet, Resnet50, and Googlenet. However, the accuracy of all predefined models was less than 80%, indicating the need to create a custom model that fits the problem statement better.

These studies demonstrate the potential of machine learning and image processing techniques in detecting and identifying counterfeit currency notes. However, further research is needed to improve the accuracy and reliability of these methods.

III. DATASET

In order to evaluate the proposed model for identifying fake currency notes using convolutional neural network (CNN), we have collected our own dataset. The entire dataset was captured using a mobile camera. The dataset comprises of images of both real and fake currency notes of denominations 10, 20, 50, 100, 200, 500, and 2000 Indian rupee. The dataset consists of a total of 377 images, divided into training and testing datasets. The training dataset has 307 images, with 179 images of real currency and 128 images of fake currency. Similarly, the testing dataset has 70 images, with 35 images of real currency and 35 images of fake currency. The dataset is diverse and includes multiple denominations, making it suitable for training and testing the proposed model. The images were captured in different lighting conditions and angles to ensure the model's robustness in detecting fake currency notes under various scenarios. We believe that this dataset will serve as a valuable resource for researchers working in the field of fake currency note detection using deep learning and computer vision techniques.



Figure 1: Real Currency Dataset



Figure 2: Fake Currency Dataset

IV. PROPOSED SYSTEM

Our proposed system for currency note detection involves several steps :

1. Dataset collection: Collect all currency notes of every denomination, both fake and real, and split them into 80% training and 20% testing datasets.
2. Pre-processing: Convert RGB images to grayscale images and apply Gaussian blur to remove any blurriness.
3. Edge detection and adaptive thresholding: Apply an edge detection algorithm and use adaptive thresholding to segment foreground and background of images, then convert to binary images.
4. Training and testing: Train the dataset on a custom CNN model and test the accuracy. Extract features of the dataset to identify the difference between real and fake notes.
5. Accuracy calculation: Calculate training and testing accuracy to determine the performance of the system.

6. GUI development: Create a Graphical User Interface (GUI) to allow users to input an image, perform feature matching, and provide output indicating whether the note is real or fake.

This proposed system has the potential to improve the accuracy and reliability of currency note detection using deep learning and image processing techniques.

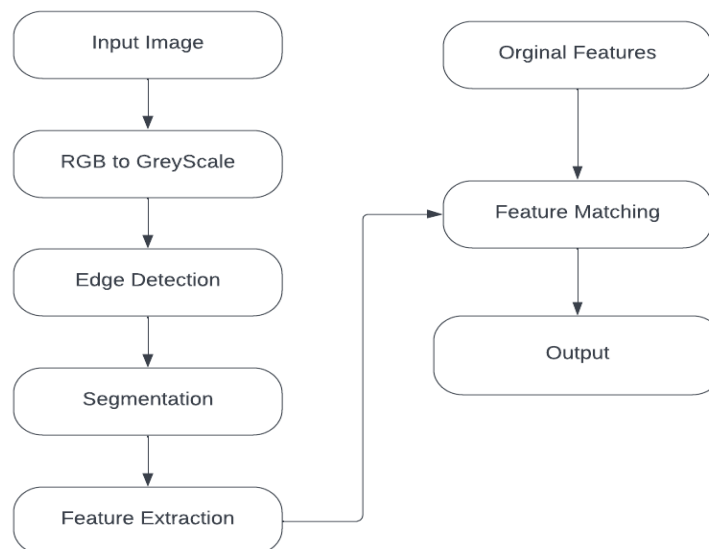


Figure 3: System Flow Chart

V. CNN MODEL

The proposed model is a Convolutional Neural Network (CNN) used for image classification. It consists of several layers that perform different operations on the input image. It consists of convolutional layers followed by max-pooling layers which help in extracting features from the images. The model has a total of four convolutional layers, each with increasing number of filters for better feature extraction. The final output layer is a sigmoid layer which gives the probability of the input image being either real or fake. The model uses the binary crossentropy loss function and RMSprop optimizer for efficient training. It also includes a dropout layer to prevent overfitting of the model. This model is specifically designed to classify currency notes as real or fake based on the given dataset.

The first layer is a Conv2D layer with 32 filters, each of size (3, 3), and ReLU activation function. This layer takes an input image of size (250, 250, 3) and applies the 32 filters to produce 32 feature maps. The second layer is a MaxPooling2D layer that performs down-sampling by taking the maximum value of each 2x2 sub-region of the feature maps produced by the previous layer. The next two Conv2D and MaxPooling2D layers are similar to the first two layers but with 64 and 128 filters respectively. The last Conv2D layer has 128 filters, followed by a MaxPooling2D layer. The output of the last MaxPooling2D layer is flattened into a vector and fed into a fully connected (Dense) layer with 512 neurons and ReLU activation function. A dropout layer with a rate of 0.5 is added to reduce overfitting.

Finally, a single neuron with sigmoid activation function is used as the output layer to predict the probability of the input image being fake or real. The model is trained using binary cross-entropy loss function and RMSprop optimizer with a learning rate of 1e-4. The performance of the model is evaluated using accuracy as the metric.

This model is specifically designed to classify currency notes as real or fake based on the given dataset.

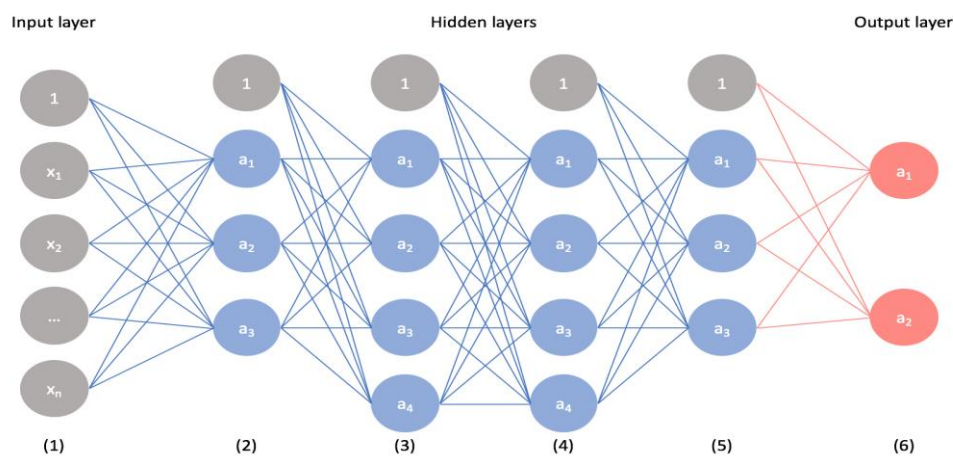


Figure 4: Layers of CNN [6]

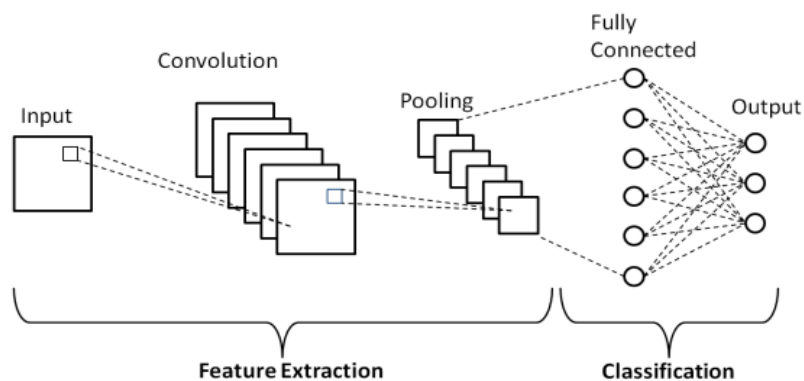


Figure 5: Convolution Neural Network [7]

VI. EXPERIMENTAL RESULTS

In order to evaluate the performance of the proposed model, the metric of accuracy was used. The model was trained on the dataset containing both fake and real currency notes of denominations 10, 20, 50, 100, 200, 500, and 2000, which was split into 80% training and 20% testing datasets. After the model was trained, its accuracy was calculated for both the training and testing datasets.

The results show that the proposed model achieved a high level of accuracy. The training accuracy was found to be 97.72%, indicating that the model was able to accurately classify the majority of the images in the training dataset. The testing accuracy was also found to be high, at 92.31%. This indicates that the model was able to generalize well to new images that were not included in the training dataset. These results suggest that the proposed model is a reliable and effective method for detecting fake currency notes.

However, it is important to note that the dataset used in this study was collected using a mobile camera and may not be representative of all types of currency notes or all possible imaging conditions. Further research could explore the performance of the proposed model using larger and more diverse datasets, as well as under different lighting and imaging conditions.

VII. CONCLUSION

In this project, we presented a methodology for the identification of real and fake currency notes using computer vision and deep learning techniques. We collected a dataset of 377 images captured using a mobile camera, containing real and fake currency notes of various denominations. The dataset was preprocessed by converting the RGB images to grayscale and applying a Gaussian blur to remove any blurriness. The edge detection algorithm was applied to segment the foreground and background of the images and convert them into binary images.

We developed a custom convolutional neural network (CNN) model using Keras with the TensorFlow backend to classify the currency notes as real or fake. The model architecture consisted of four convolutional layers

followed by a fully connected layer and an output layer. The model was trained on the preprocessed dataset and achieved a training accuracy of 97.72% and a testing accuracy of 92.31%. The results showed that the proposed methodology is effective in distinguishing real and fake currency notes with high accuracy.

In conclusion, the proposed methodology can be applied in real-world scenarios for the detection of fake currency notes. It can be further enhanced by increasing the size of the dataset and using more advanced pre-processing techniques. Overall, the combination of computer vision and deep learning techniques can play a vital role in addressing the issue of counterfeit currency and ensuring the integrity of the financial system.

VIII. REFERENCES

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