International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 05 | May - 2023 SJIF 2023: 8.176 ISSN: 2582-3930

Fake Currency Detection using Deep Learning And Image Processing

Dr. Madhuri Borawake, Umesh ManePatil,
Prasad Suryawanshi, Cinthiya Salve,
Abhishek Karale
Computer Engineering Department,
PDEA'S College Of Engineering Manjari(BK), India

ABSTRACT – This project focuses on the detection of fake currency using Machine Learning. The aim is to develop a mobile application that automates this process. The methodology involves image acquisition, image segmentation, feature extraction, and comparison. A magnified image of the genuine currency is used to create a dataset for machine learning. The features of the currency note being tested are compared with the dataset to determine its authenticity. The key challenge is to systematically repeat the analysis process to minimize errors and reduce time.

The Automatic Fake Currency Recognition System is designed to identify counterfeit paper money and distinguish it from genuine currency. The issue of fake currency has had a significant impact on the financial system and various sectors, particularly after demonetization. This approach explores a new method using Convolutional Neural Networks (CNNs) to identify fake money through image analysis, which is found to be superior to previous image processing techniques. Deep Learning, which has shown remarkable results in image classification tasks, forms the basis of this technique. It enables real-time identification of counterfeit currency through image recognition, benefiting both individuals and machines. The proposed system's accuracy is evaluated using precision.

Keywords: Convolutional Neural Networks, Counterfeit, Demonetization, Image Processing, Deep Learning, Vgg16, Automatic detection.

1. INTRODUCTION

Currency duplication, also known as counterfeit currency, poses a significant threat to the economy. With advancements in printing and scanning technology, the production of fake notes has become a common phenomenon. The increased circulation of counterfeit currency has become a serious problem for the country. The Reserve Bank of India estimates that there is approximately Rs. 2 trillion worth of fake rupee notes in circulation throughout India. While various methods for detecting fake notes exist worldwide, most of them are hardware-based and expensive. These machines are primarily available in banks and are not easily accessible to the average citizen. Given the severity of the problem, there is a pressing need for a more convenient solution.

The Fake Currency Detection App has been developed to address this issue by enabling users to identify fake currency through their smartphones. As the number of Android mobile phone users continues to grow in the country, providing an Android application for fake currency detection is a practical and effective idea. The app is specifically designed to check Indian currency notes and coins, providing users with real-time feedback on the authenticity of the currency.

There is an urgent requirement for an easier method to distinguish between genuine and counterfeit banknotes. The verification of counterfeit bills plays a crucial role in various applications, including automated merchant product machines and vending machines. Our proposed framework for banknote verification consists of six stages: image acquisition, grayscale conversion, edge detection, highlight extraction, image slicing, and data analysis. Automated machines, commonly found in banks and small shops, greatly benefit from the ability to detect counterfeit banknotes. With the implementation of this machine, the process of verifying banknotes becomes less complicated and more efficient. Using banknotes as a medium for trading and managing goods has become one of the primary options in the current market.

By employing the Fake Currency Detection App and implementing efficient verification methods, we can significantly reduce the circulation of counterfeit currency and safeguard the financial system from the detrimental effects of fake notes.

1.1 Commonly Used Methods to Detect Fake Notes

i. See Through Register: A small floral design is printed in the center of the vertical band and adjacent to the watermark. The floral design on the front is hollow, while the back is filled. This design exhibits back-to-back registration, appearing as a single floral design when held against light.

ii. Watermarking: The banknotes feature a watermark of Mahatma Gandhi. The Mahatma Gandhi watermark includes a shading effect and multidirectional lines within the watermark.

iii. Optically Variable Ink: The security feature of optically variable ink is employed in the Rs. 200, Rs. 500, and Rs. 2000 banknotes. The denomination value is printed using this ink, which exhibits a color change effect. When the note is held flat, the numerical values of 2000 or 500 appear green, but they change to blue when viewed at an angle.

iv. Fluorescence: Number panels on the notes are printed with fluorescent ink, and the notes also incorporate optical fibers. The number panel in fluorescent ink and the presence of optical fibers can be observed under UV light.

v. Security Thread: The 2000- and 500-rupee notes contain a security thread positioned to the left of Mahatma Gandhi's portrait. The security thread displays visible features of RBI and BHARAT. When the note is held against light, the security thread appears as a continuous line.

vi. Latent Image: A latent image representing the respective denomination value is present on the right side of Mahatma Gandhi's portrait on the vertical band of the notes. When the note is held horizontally at eye level, the latent image becomes visible.

vii. Micro Lettering: Micro letters are located between the portrait of Mahatma Gandhi and the vertical band. These micro letters display the denomination value of the banknote and can be seen clearly under a magnifying glass.

viii. Identification Mark: Each banknote possesses a unique identification mark. Different shapes of identification marks are used for various denominations (H for Rs. 200, circle for Rs. 500, and square for Rs. 2000). The identification mark is positioned to the left of the watermark.

Figure.1. Security Features of Indian Currency

2. LITERATURE SURVEY

Gouri Sanjay Tele et al. [5] conducted research on the detection of counterfeit Indian currency. They emphasized the importance of security features such as watermarks, latent images, security threads, and optically variable ink in determining the authenticity of banknotes. Their method focused on extracting latent image properties and identifying ID marks from currency images using image processing techniques.

Navya Krishna G, et al. [6] proposed an Automatic Fake Currency Recognition System (AFCRS) using Convolutional Neural Networks (CNNs). They highlighted the impact of demonetization on the financial system and various sectors, motivating the need for effective counterfeit detection. Their approach utilizing CNNs for fake note identification showed better results compared to previous image processing methods. Deep Learning, specifically CNNs, demonstrated significant achievements in image classification tasks, enabling real-time detection of counterfeit currency through image analysis. The proposed AFCRS system could be deployed as a smartphone application to assist the general public in identifying fake notes.

N.A.J Sufri et al. [7] developed a vision-based system for banknote recognition using different machine learning and deep learning approaches. They utilized RGB values as features and applied algorithms such as Decision Trees (DT), Naive Bayes (NB), k-Nearest Neighbors (kNN), Support Vector Machines (SVM), and the deep learning model AlexNet. Both kNN and DT achieved a high accuracy rate of 99.7%, while SVM and BC outperformed them with 100% accuracy.

Veeramsetty et al. [8] introduced a lightweight Convolutional Neural Network (C-NN) system for recognizing Indian currency notes in web and cellphone applications. They created a dataset of 4657 images, including different denominations of currency notes. Data augmentation techniques were applied to increase the dataset size, and the resized images were used as inputs to the C-NN model. Their proposed model outperformed existing architectures in terms of training and testing accuracies.

Chowdhury et al. [9] proposed an automatic banknote recognition system using image processing and deep learning techniques. They collected images from scans and photographs of genuine banknotes. Two approaches were employed: feature extraction and classification using K-Nearest Neighbors (KNN), and utilizing a convolutional neural network (C-NN) with a dense layer and softmax classifier. The KNN approach achieved 91% accuracy, while the C-NN approach achieved a perfect accuracy rate of 100%.

Ali et al. [10] developed a machine-assisted system called Deep Money for recognizing counterfeit banknotes. They utilized Generative Adversarial Networks (GANs), an unsupervised learning approach, for training the system. Pakistani banknotes were used in their experiments, and image processing and feature recognition methods were applied. Their GANs-based technique achieved an accuracy rate of 80% in detecting fake currency.

Laavanya et al. [11] focused on security thread extraction for counterfeit money identification. They employed transfer learning with AlexNet, a widely used deep neural network architecture. Augmentation techniques were used to increase the database size, and the MATLAB 2018a software was utilized. The transfer trained AlexNet model with Adam optimization showed promising results in detecting counterfeit currency.

III. BLOCK DIAGRAM

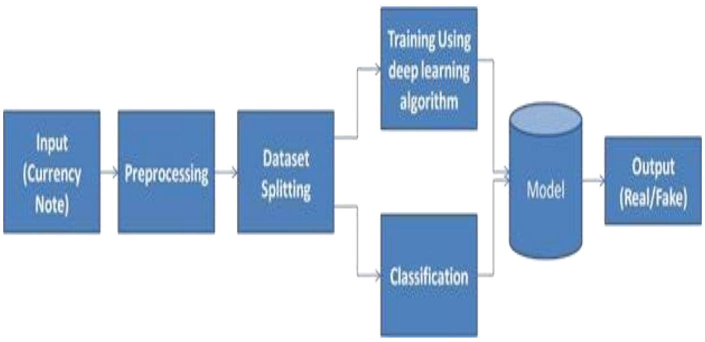

Fig. 2 Block diagram of the proposed system

a. Data Collection

To create a genuine and counterfeit dataset, a step-by-step process is followed. Banknotes of different denominations (10, 20, 50, 100, 200, 500, and 2000) are considered for evaluation. The photographs of the banknotes are taken using a phone camera with a resolution of 12 MP under various lighting conditions. For evaluation purposes, both genuine and forged banknotes are obtained. The examples below illustrate genuine and counterfeit banknotes.

Fig.3 (a) Real note

Fig.3 (b) Fake note

b. Pre-processing

During image capture, there is inherent noise that needs to be removed through preprocessing. The proposed approach utilizes the center channel to eliminate salt and pepper noise. Intermediate filtering, a crucial non-linear process, reduces artifacts and noise while preserving image edges. Random errors in corresponding channels can result in hasty or erroneous conclusions. In the intermediate channel, a sliding window technique is employed, where the average intensity of pixels within the window determines the intensity of the processed pixel.

c. Training with CNN

Convolutional Neural Networks (CNNs) have proved to be highly effective in tasks such as image verification and classification. A CNN is a type of feedforward neural network that comprises multiple layers. It consists of channels or neurons with adjustable weights, biases, and thresholds. Each channel receives input, performs convolution, and applies non-linear activation functions. The typical CNN architecture involves convolution, pooling, rectified linear units (ReLU), and fully connected layers, as depicted in Figure 4.

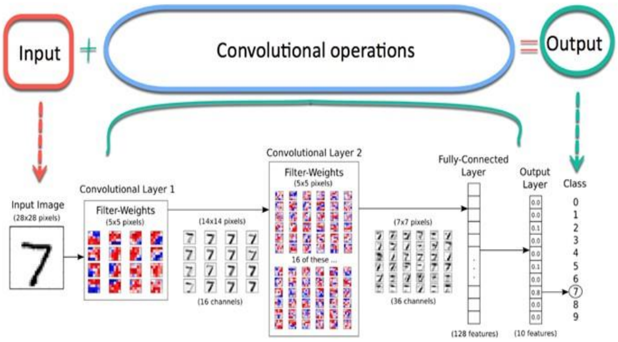

Fig 4. Architecture of CNN

1. Convolutional Layer

The Convolutional layer serves as the fundamental building block in a Convolutional Network and handles a significant portion of the computational workload. Its primary function is to extract features from the input data, which in this case is an image. Through convolution, the layer maintains the spatial relationship between pixels by utilizing small squares of the input image to learn image features. The input image is convolved with a set of trainable neurons, resulting in a feature map or activation map. These feature maps then serve as input to the subsequent Convolutional layer. It is numerically addressed as:

$G[m,n]=(f*h)[m,n]=\sum j\sum kh[j,k]f[m-j,n-k]Gm,n=f*$
$hm,n=\sum j\sum khj,kf[m-j,n-k]$………(1)

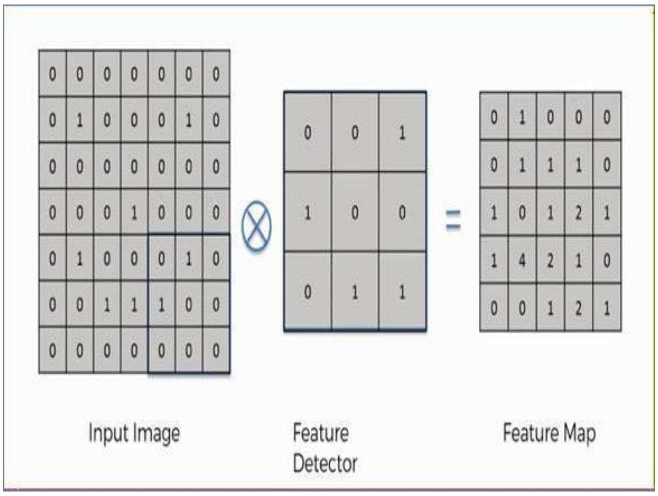

Fig 5. Convolutional Layer

2. ReLU Layer

ReLU is a non-linear activity and contains units that use rectifiers. A per-component activity means that it is applied per-pixel and does nothing to restore all bad properties in the element map. To understand how ReLU works, we have a neuron input designated as x, and the resulting rectifier is expected to be shown as

$f(x)=\max(0,x)f(x)=\max(0,x)$).)……(2)

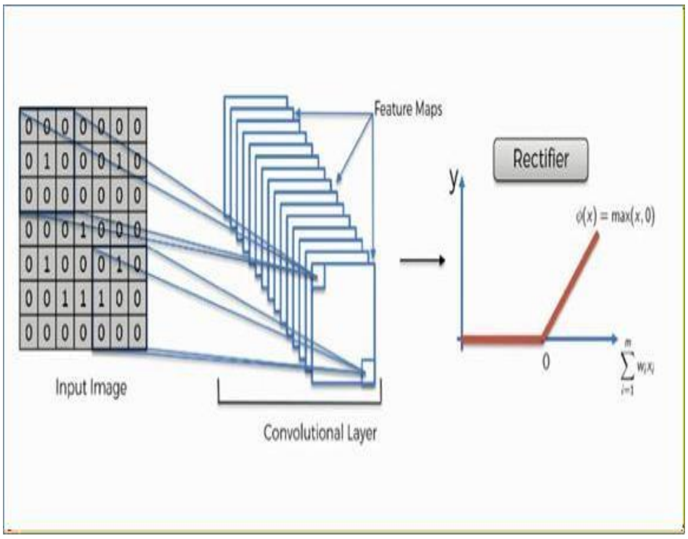

Fig 6. ReLU

3. Pooling Layer

The Pooling Layer reduces the dimensionality of each Initiation Card, but retains the most basic data. The info image is divided into a series of discreet squares. Each district is inspected by indirect activities such as normal or most extreme. This layer allows for better inference, faster assembly, and better interpretability, and distortions are typically placed between convolutional layers.

The max pooling layer is very simple and does not learn itself. Getting the k×kk×k locales will give you the largest single value there. For example, if those feedback layers are N×NN×N layers, then each k×kk×k block is reduced to a single value by the maximum capacity, thus producing Nk×NkNk×Nk layers.

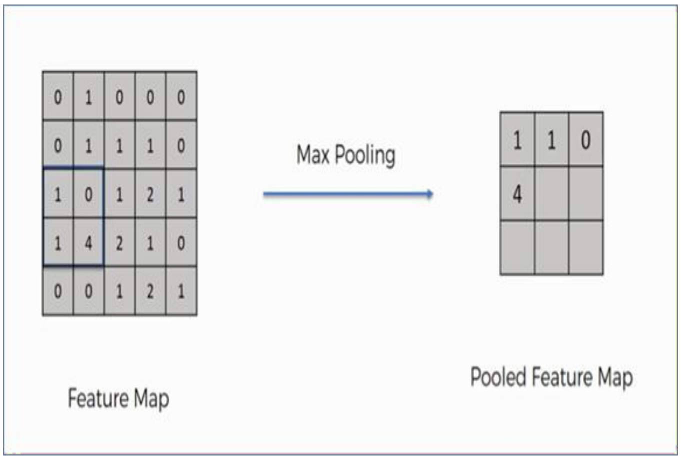

Fig 7. Max Pooling

4. Flatten Layer

After completing the past two stages, we must always have a pooled highlight map at this time. because the name of this progression suggests, we are going to straighten our pooled highlight map into a bit like within the picture beneath.

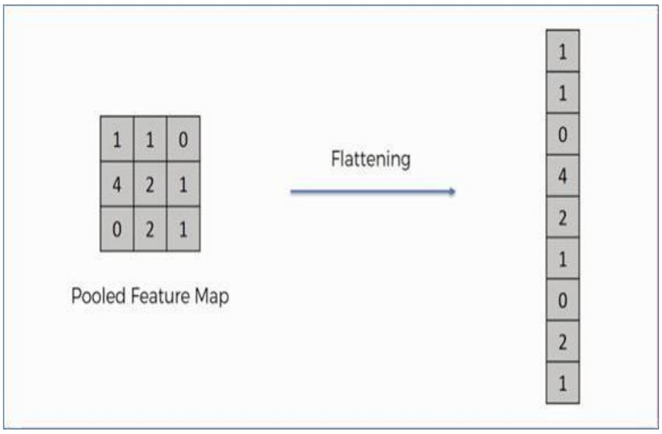

Fig 7. Flattening Layer

5. Fully Connected Layer

The purpose of using the FCL is to use these highlights to characterize information images into different classes based on a prepared data set. FCL is seen as the final pooling layer that handles the highlighting of classifiers that utilize SoftMax transformation work. The resulting probability number from a fully mapped layer is 1. This is often ensured by including SoftMax in the activation work. What SoftMax does is take a vector of inconsistent real ratings and squash them into a vector of values somewhere between zero and sum to one.

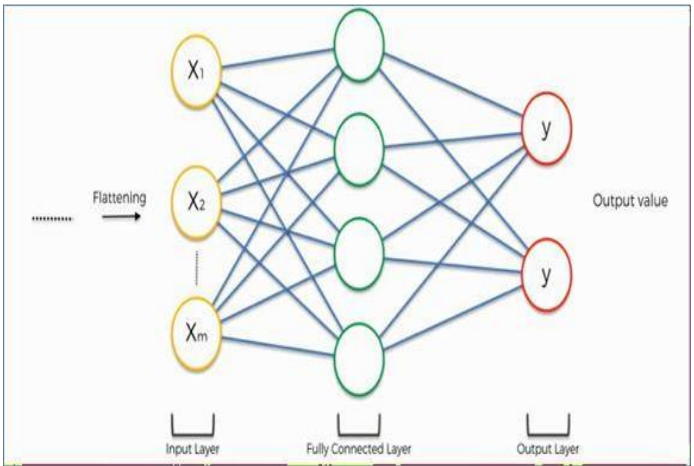

Fig 8. Fully Connected Layer

• Qualitative Analysis:

The objective of chemical analysis is to provide a comprehensive interpretation of individual presentations. Instead of relying on frequency-based analysis of etymological elements found in the data, equal consideration is given to both common and uncommon features. Fine differentiation is deemed appropriate as subjective analysis does not require a limited number of classifications. It is important to acknowledge the inherent ambiguity of human language in examinations. Figure 6.1 illustrates examples of input images of 10, 20, 50, 100, 500, and 2000 bills.

• Quantitative Analysis:

This approach involves categorizing and quantifying inclusions, as well as developing models to comprehend more significant information. The findings are often aggregated into larger populations, establishing direct correlations between the two datasets using appropriate testing and significance methods. Through quantitative analysis, we can determine which features are likely genuine reflections of language or set behavior, and which ones are mere possibilities. By examining isolated language samples, we can identify the frequency and anomalies of specific characteristics, thereby determining their overall commonality or irregularity. Precision limits are utilized to specify the quantitative studies in the proposed framework.

V. SYSTEM REQUIREMENTS

Hardware Specifications:

- Processor speed: 500Mhz or above
- Processor - Intel (R) Core (TM) i3
- Installed RAM - 4 GB or More
- HDD – 80GB
- I/O – Desktop, Keyboard & Mouse

Software Specifications:

Operating System - Windows 7/8/10

- Programming Lang. and tools – Android Studio, OpenCV, Python, Flask server,
- Latest Android App running device or mobile (basic version 4.2.2 or afterwards)

VI. IMPLEMENTATION

The primary objective of this project is to detect counterfeit currency using Machine Learning. The aim is to automate this process using a mobile application. The underlying logic involves image acquisition, image segmentation, feature extraction, and comparison. The enlarged image of the authentic currency serves as the dataset for machine learning. By comparing the features of the currency note being tested with the dataset created from the genuine magnified image, it can be determined whether the note is genuine or counterfeit. The main challenge lies in conducting the analysis process systematically and methodically to minimize errors and save time. Each dimension quantifies the dissimilarity between the image being examined and a designated prototype. To assess the dissimilarity between two images, local key points are detected and described on each image. By considering the characteristics of the currency, matched key points between the two images can be efficiently identified. Additionally, a post-processing procedure is proposed to eliminate mismatched key points.

Software Libraries Used:

- OpenCV
- Imutils
- Numpy
- Pillow

Software Specification:

Python

Python is a popular interpreted high-level general-purpose programming language. It is known for its emphasis on code readability, achieved through significant indentation. Python supports multiple programming paradigms, including structured, object-oriented, and functional programming. It is dynamically-typed and includes garbage collection. One of Python's strengths is its extensive standard library, often referred to as a "batteries included" feature.

Python Idle

Python IDLE, or Integrated Development and Learning Environment, is a basic tool that comes bundled with Python installations. It serves as an IDE (Integrated Development Environment) and provides a simple interface for writing code. Python IDLE is particularly suitable for beginners and is available on Windows and Mac platforms. Linux users can typically obtain Python IDLE through their package manager. It can be used both as an interactive interpreter and as a file editor.

OpenCV

OpenCV is a huge open-source library for computer vision, machine learning, and image processing. OpenCV supports a wide variety of programming languages like Python, C++, Java, etc. It can process images and videos to identify objects, faces, or even the handwriting of a human. When it is integrated with various libraries, such as Numpy which is a highly optimized library for numerical operations, then the number of weapons increases in your Arsenal i.e whatever operations one can do in Numpy can be combined with OpenCV OpenCV is a huge open-source library for computer vision, machine learning, and image processing. OpenCV supports a wide variety of programming languages like Python, C++, Java, etc. It can process images and videos to identify objects, faces, or even the handwriting of a human. When it is integrated with various libraries, such as Numpy which is a highly optimized library for numerical operations, then the number of weapons increases in your Arsenal i.e whatever operations one can do in Numpy can be combined with OpenCV It is used for:

• Reading an image
• Extracting the RGB values of a pixel
• Extracting the Region of Interest (ROI)
• Resizing the Image
• Rotating the Image
• Drawing a Rectangle
• Displaying text

Imutils

Imutils are a series of convenience functions to make basic image processing functions such as translation, rotation, resizing, skeletonization, and displaying Matplotlib images easier with OpenCV.

Numpy

NumPy is a Python library used for working with arrays. It also has functions for working in domain of linear algebra, fourier transform, and matrices.In Python we have lists that serve the purpose of arrays, but they are slow to process. NumPy aims to provide an array object that is up to 50x faster than traditional Python lists. The array object in NumPy is called ndarray, it provides a lot of supporting functions that make working with ndarray very easy. Arrays are very frequently used in data science, where speed and resources are very important.

VI. FUTURE ENHANCEMENTS

Many different adaptations, tests and innovations have been kept for the future due to the lack of time. As future work concerns deeper analysis of particular mechanisms, new proposals to try different methods or simple curiosity.

1. In future we would be including a module for currency conversion.
2. We can implement the system for foreign currencies.
3. Tracking of device's location through which the currency is scanned and maintaining the same in the database.

VI. REULTS

APP IMAGES:

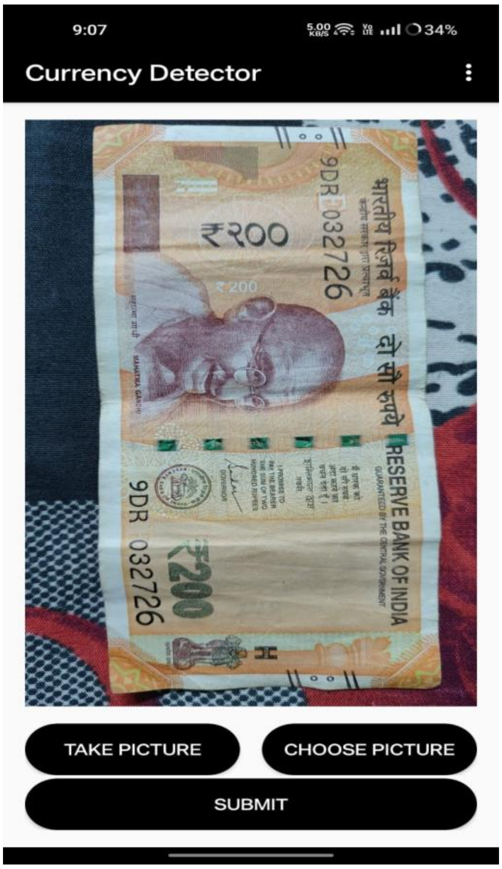

Fig. Scanning Currency Note

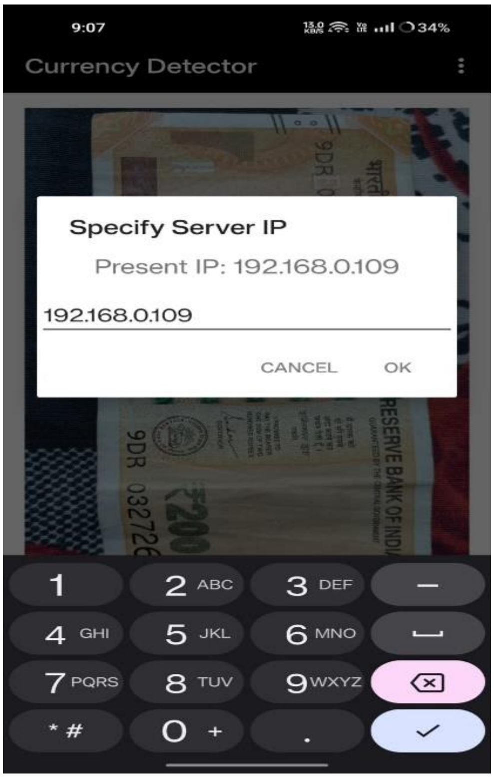

Fig. Specifying IP address

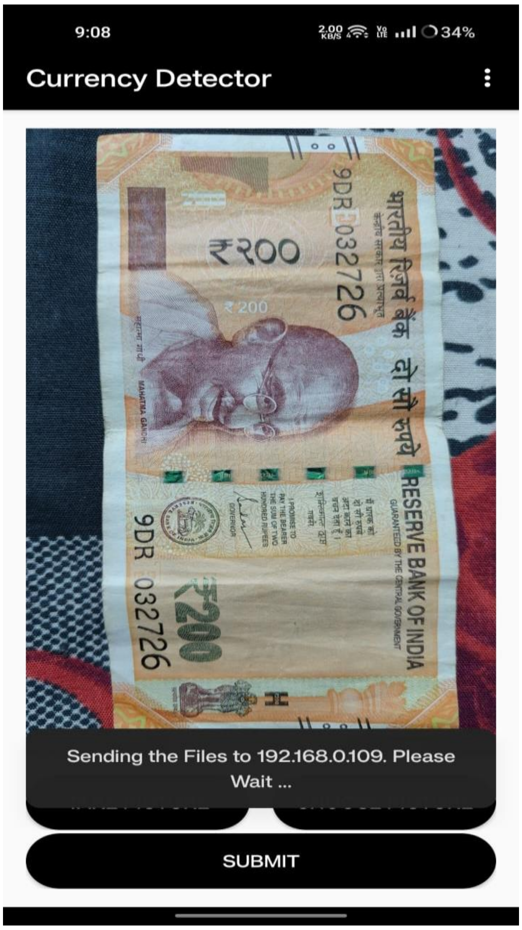

Fig. Sending Note to Server for Detection

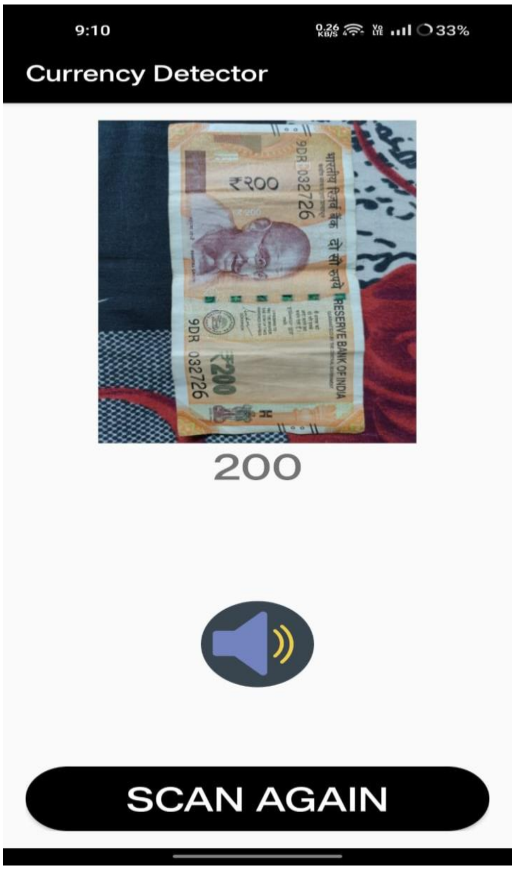

Fig. Output Result of Detection

VI. COCLUSION

In this project, we aim to develop a currency recognition system for Indian paper currency using OpenCV techniques in the Python language. By utilizing the ORB model, brute force matcher, and KNN matching techniques, we have achieved an efficient approach for currency detection. The system provides quick and accurate results, making it a valuable and cost-effective solution for various users. The image cropping and uploading process is meticulously executed, ensuring optimal performance. Furthermore, the system can successfully extract features even when there are variations in size between the test images and the input images provided by the user. Additionally, the system excels at accurately identifying the denominations of Indian paper currency.

Our approach involves employing image processing principles to detect fake Indian currency notes. The system is designed to be affordable and capable of detecting denominations of 10, 20, 50, 100, 500, and 2000 for Indian currency. It delivers precise and reliable results, with a quick and straightforward fake note detection process. The system takes input through a camera and displays the output on a laptop screen and a mobile application. For training and testing the detection of fake currency, we utilize CNN and Vgg16 algorithms. The qualitative and quantitative analysis of the proposed system indicates that the Vgg16 algorithm outperforms the CNN algorithm.

While our current implementation considers the entire currency image, future enhancements will focus on incorporating all the security features of currency through appropriate structural design and suitable training data. Moreover, noise present in captured images will be addressed as a preprocessing step in the currency detection process. The recognition and detection of fake currency can be further improved by considering the patterns on the currency surface as additional features.

VI. ACKNOWLEDGEMENT

On this remarkable occasion of successfully completing the project on fake Indian currency notes using deep learning, I would like to express my heartfelt appreciation to all the teachers and mentors who have provided invaluable guidance and support to our group, ensuring that we stayed on the right path to achieve our objectives.

I am also grateful for the assistance and cooperation of all the team members involved. Their contributions have been instrumental in our progress, and I firmly believe that together we can accomplish even greater things in our future endeavors.

VI. REFERENCES

[1] Sonali R. Darade, Prof. G. R. Gidveer, “Automatic Recognition of Fake Indian Currency Note”, 2016 International Conference on Electrical Power and Energy Systems (ICEPES) Maulana Azad National Institute of Technology, Bhopal, India. Dec 15-16, 2016

[2] Ingulkar Ashwini Suresh1, Prof. P. P. Narwade, “Indian Currency Recognition and Verification Using Image Processing”, International Research Journal of Engineering and Technology (IRJET) Volume: 03 Issue: 06, June-2016

[3] Gouri Sanjay Tele, Akshay Prakash Kathalkar, Sneha Mahakalkar, Bharat Sahoo, and Vaishnavi Dhamane. ‘Detection of fake Indian currency’. International Journal of Advanced Research, Ideas, and Innovations in Technology, 4(2):170–176, 2018.

[4] Naga Sri Ram B Yamini Radha V Rajarajeshwari P Navya Krishna G, Sai Pooja G. “Recognition of fake

currency note using convolutional neural networks". 4(2):182–186, 2018.

[5] N. A. J. Sufri, N. A. Rahmad, N. F. Ghazali, N. Shahar, and M. A. As'ari. "Vision based system for banknote recognition using different machine learning and deep learning approach". In 2019 IEEE 10th Control and System Graduate Research Colloquium (ICSGRC), pages 5–8, 2019.

[6] Veeramsetty, V., Singal, G. and Badal, T. (2020) "Coinnet: platform independent application to recognize Indian currency notes using deep learning techniques", Multimedia Tools and Applications, 79(31–32), pp. 22569– 22594.

[7] Chowdhury, U. R., Jana, S. and Parekh, R. (2020) 'Automated System for Indian Banknote Recognition using Image Processing and Deep Learning, in 2020 International Conference on Computer Science, Engineering and Applications, ICCSEA 2020, pp. 1–5.