IJRAR.ORG E-ISSN: 2348-1269, P-ISSN: 2349-5138

INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS (IJRAR) | IJRAR.ORG

An International Open Access, Peer-reviewed, Refereed Journal

Machine Learning Based- Fake Currency Detection Using SVM and KNN

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Abstract: The rapid advancement of technology has led to an increase in counterfeit currency circulation, posing significant financial risks. Conventional techniques for detecting counterfeit goods are frequently laborious and prone to human error. To address this issue, this study presents a Machine Learning-Based Fake Currency Detection System utilizing Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) algorithms. Tsshe proposed model extracts key features from currency images, such as texture, edges, and other distinguishing characteristics, to classify them as genuine or counterfeit. SVM is employed for its ability to create optimal decision boundaries, while KNN provides a comparative classification approach based on similarity measures. High-resolution pictures of both genuine and counterfeit cash make up the training and testing dataset. Experimental results demonstrate that the hybrid approach achieves high accuracy in distinguishing counterfeit notes, making it an efficient and reliable solution for real-world applications.

***Index Terms* - Counterfeit currency, machine learning, Support Vector Machine (SVM), K- Nearest Neighbor (KNN), feature extraction, hybrid model.**

I. INTRODUCTION

Counterfeit currency is a growing challenge that affects economies worldwide, leading to financial losses and disrupting market stability. Traditional methods of detecting fake bills, such as manual inspection and ultraviolet (UV) light verification, are often inefficient, time-consuming, and prone to human error. With advancements in technology, machine learning-based approaches have emerged as effective solutions for improving counterfeit detection accuracy and reliability. This study explores the application of Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) algorithms for fake currency detection. SVM is a powerful supervised learning algorithm known for its ability to create optimal decision boundaries for classification tasks. On the other hand, KNN is a simple yet effective classification technique that determines the category of a new sample based on the majority class of its nearest neighbors. By combining these methods, the proposed system enhances the accuracy and robustness of fake bill detection. The system analyses key currency features such as texture patterns, edge detection, and geometric structures, extracting relevant data to differentiate between genuine and counterfeit notes. A dataset comprising images of real and fake banknotes is used for model training and evaluation. The performance of SVM and KNN classifiers is compared to determine the most efficient approach for real-world applications. This research aims to provide a cost-effective, automated, and highly accurate solution for financial institutions, businesses, and individuals to detect counterfeit currency efficiently.

The implementation of machine learning in counterfeit detection strengthens fraud prevention mechanisms, contributing to financial security and economic stability. Technology is growing very fast these days. As a result, the banking industry is also becoming more modern every day. Automatic false cash detection in automated teller machines and automated goods sellers is therefore desperately needed. The development of a reliable and effective automatic cash identification machine has inspired numerous researchers. However, this method is useless if the note is torn. A note's hue characteristic changes significantly if it is filthy. Therefore, how we extract the image's attributes and use the right method to increase the note's recognition accuracy is crucial. In essence, the goal of currency identification technology is to recognize and extract both visible and unseen characteristics from banknotes. Numerous methods have been put forth up to this point to identify the currency note. For example, color and size.

However, if the note is ripped or soiled, this method is useless. A note's hue characteristic changes significantly if it is filthy. Therefore, how we extract the image's attributes and use the right method to increase the note's recognition accuracy is crucial.

II. LITERATURE REVIEW

[1] In the International Journal of Applied Engineering Research, the authors proposed a deep learning-based counterfeit bill detection algorithm using a convolutional neural network (CNN). The model includes two convolutional layers with ReLU and max-pooling, and two fully connected layers with dropout and a SoftMax output. The study used real and counterfeit bills created using three different laser printers (Konica C250, Canon iRc3200N, Canon iRC2620), resulting in a dataset of 21,600 samples. Experimental results demonstrated that the proposed model achieved up to 100% detection accuracy after 30 epochs, outperforming traditional feature-based methods using techniques like Wiener filtering and non-local averaging.

[2] In the Rose-Hulman Undergraduate Mathematics Journal, the authors developed a machine learning-based system for identifying fake bills using bill measurements. They evaluated three algorithms—k-nearest neighbors (k-NN), perceptron, and multilayer perceptron (ANN) on a dataset of 1,500 banknotes (1,000 real and 500 fake) sourced from Kaggle. Feature inputs included diagonal measurements, side heights, margins, and length. The best-performing models, k-NN (with Manhattan distance and k=5/6) and ANN (with 2 hidden layers and tan h activation), both achieved an accuracy of 99.13% using 5-fold cross-validation. The study also analyzed feature importance using the perceptron model, identifying bill length as a key discriminator.

[3] In ICCGI 2018, the authors proposed a counterfeit bill and forgery device detection method using a CNN-based deep learning model. The model comprises two convolutional layers with ReLU activation and max-pooling, followed by two fully connected layers with dropout and a SoftMax output. The approach demonstrated nearly 100% detection accuracy for both counterfeit bills and the devices used to forge them. Experiments used images of original bills and counterfeit versions produced by three different color laser printers.

[4] In Research Square, the authors proposed a deep CNN model for detecting fake Ethiopian banknotes. Their model comprises 14 convolutional layers, two fully connected layers, and a sigmoid-based output for binary classification. Key preprocessing steps include grayscale conversion, histogram equalization, and data augmentation. The dataset consists of 6,100 images (real and fake banknotes) collected from the Commercial Bank of Ethiopia. The model achieved 99.9% training accuracy, 99.4% validation accuracy, and 97.6% testing accuracy, outperforming pre-trained VGG19 and MobileNetV2 models.

[5] In the International Journal of Research in Computer and Communication Technology, the authors reviewed traditional and image processing-based methods for detecting fake currency. They discussed watermarking, optically variable ink, UV fluorescence, micro-lettering, and security threads as standard anti-counterfeiting techniques. A MATLAB-based method was also proposed, involving color channel manipulation and correlation checks. No datasets were used in the study, and the focus was on enabling common people to identify counterfeit notes using simple image processing techniques.

[6] In the International Journal of Engineering & Technology, the authors proposed a fake currency detection system using image processing techniques implemented in MATLAB. The approach involves scanning currency images, grayscale conversion, binarization, morphological processing, blob labelling, orientation correction, and linear correlation against a reference database. A KNN-based classification system is employed to determine authenticity. The system achieved high accuracy in testing with play money, and emphasizes prevention over detection. No public dataset was used; the authors created their own set of scanned images.

[7] In MESIICON 2022, the authors proposed a hybrid semi-supervised GAN-based approach (SSPGAN) for counterfeit money detection using the Tunisian currency. The model combines parallelized and semi-supervised GANs across four denominations (5, 10, 20, 50 TND), with shared layers to improve generalization. They introduced the Tun Money dataset comprising 1,164 real and fake banknote images. The method achieved 100% accuracy and a Fréchet Inception Distance (FID) below 1, outperforming several GAN-based benchmarks like SSGAN and ACGAN.

[8] In Supremo Amicus, the author analyzed how fake bill mechanisms challenge India's GST law. The paper highlights how fraudsters exploit Input Tax Credit (ITC) provisions by creating fake companies and generating fraudulent invoices for non-existent transactions. Multiple case studies from media reports are reviewed, illustrating ITC frauds amounting to hundreds of crores. The study also details GST structures, legal provisions, penalties under CGST, and offers suggestions such as mandatory evidence submission and complaint mechanisms for fake invoices. No dataset or machine learning model was used in the analysis.

III. EXISTING METHOD

Convolutional Neural Networks (CNNs) are a foundational deep learning architecture widely used for image classification, object detection, and visual recognition tasks. CNNs are made up of several layers that automatically learn the spatial hierarchies of features from input images. Convolutional, pooling, and completely linked layers are among these layers. In object recognition systems, CNNs are trained on large datasets to detect and classify objects by extracting low-level to high-level features such as edges, textures, and object shapes. They have been successful in several domains including medical imaging, surveillance, autonomous vehicles, and assistive technologies. However, despite their powerful performance, CNNs come with several significant limitations. One major drawback is their high computational cost, especially during training. Training deep CNNs requires powerful GPUs, high memory, and extended training time, which limits their deployment on real-time or edge devices. Additionally, in order to attain high accuracy and prevent over fitting, CNNs usually need huge labelled datasets. In scenarios where data is scarce or annotation is expensive, CNNs may not perform reliably. Another key limitation is their strong dependency on image quality. Poor lighting, blurriness, occlusions, or low-resolution inputs can significantly degrade the performance of CNN-based models. For visually impaired assistive systems, this becomes critical, as inconsistent image quality can lead to detection failures or false identification. CNNs also struggle with understanding contextual relationships in cluttered scenes, which can affect recognition in real-world environments. The rigid and sequential structure of CNNs lacks dynamic adaptability and may fail to generalize well across different environments or object variations. Furthermore, CNNs often operate as black-box models, offering limited explain ability, which can be a challenge in safety-critical applications. These drawbacks highlight the need for more efficient, accurate, and interpretable models that can work well with limited resources and under varying conditions, especially for applications like assistive technologies for the visually impaired.

IV. PROPOSED METHOD

The proposed system introduces an efficient and lightweight approach for counterfeit currency detection using machine learning techniques Support Vector Machine (SVM) and K-Nearest Neighbor (KNN). The system focuses on extracting key features from currency notes such as texture, edge patterns, and print quality using image processing techniques. The SVM and KNN classifiers then employ these retrieved features as input. SVM works by identifying the optimal hyper plane that separates real and fake currency samples with maximum margin, while KNN classifies each sample based on the majority label among its nearest neighbors. The combination of these models ensures robustness in handling different variations in currency notes. Unlike deep learning models that require large datasets and high computational power, this system is designed to perform well even with limited data and basic hardware. The use of traditional machine learning allows for easier implementation and faster processing, making it suitable for real-time applications. The system can be integrated into mobile or embedded devices for instant detection at points of sale or banks. The lightweight nature of the classifiers enables real-time response with minimal delay. This approach ensures effective detection across varying conditions such as worn-out or slightly damaged notes. The system also supports scalability, allowing future upgrades to include new currencies or features. The goal is to make currency verification more accessible, affordable, and dependable without the need for complex infrastructure. This solution is ideal for developing regions where counterfeit detection systems are often lacking. Overall, the method delivers a smart, adaptable, and accurate system for counterfeit detection using SVM and KNN.

4.1 BLOCK DIAGRAM

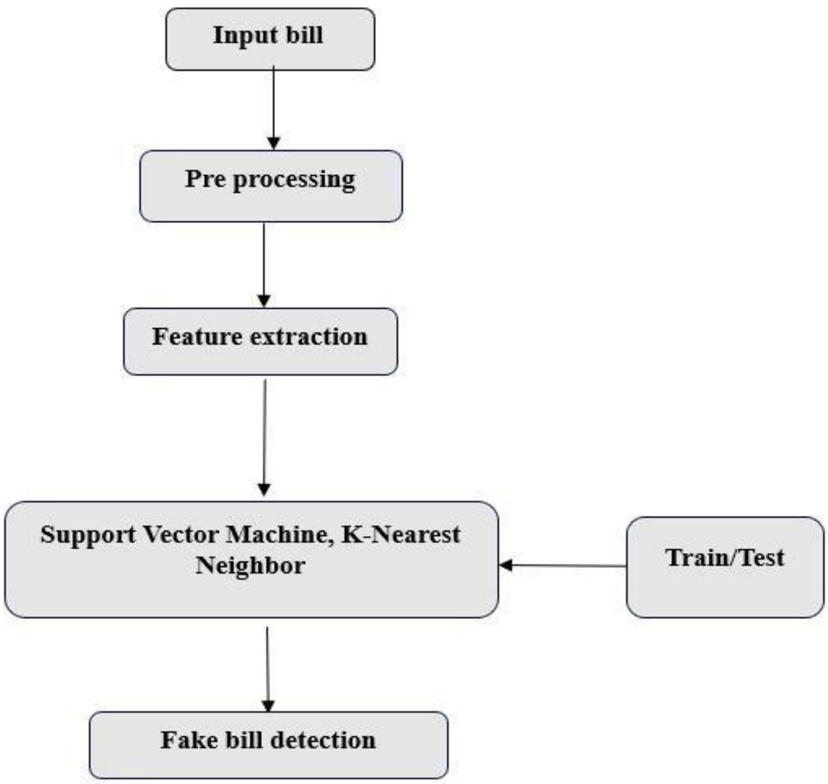

Fig No 1: Block Diagram

4.2 Working

4.2.1 Load Database of Fake Currency Images

Loading the database of pictures of actual and counterfeit money notes is the initial stage. These images are typically collected from sources such as public datasets or scanned currency notes from various regions. The images are organized into separate folders or labelled with real or fake tags. A script is used to read these images and store them as an array of pixel values, which can be processed further. This dataset is essential for developing precise classifiers and forms the basis of the machine learning models.

4.2.2 Preprocess the Data

Once the dataset is loaded, it undergoes pre-processing, which includes resizing images to a standard size, converting them to grayscale (if necessary), and normalizing pixel values to a consistent range (typically 0 to 1). Image enhancement techniques like noise reduction or edge detection may also be applied to improve feature extraction. Data augmentation (such as rotation, flipping, and cropping) can be employed to artificially increase the dataset size and ensure the model generalizes better to unseen data. This step is essential for improving the model's ability to handle various image distortions and variations.

4.2.3 Data Visualization

Data visualization plays a key role in understanding the dataset and identifying potential issues like imbalances between real and fake currency images. Tools like Matplotlib or Seaborne are used to plot graphs or display sample images to visually inspect their quality and diversity. Histograms, pie charts, or bar graphs can be generated to show the distribution of classes (real vs. fake) in the dataset. Visualizing image samples also helps ensure that the images are correctly labelled and appropriately processed before training the models. Gaining knowledge about the features of the dataset is facilitated by this stage.

4.2.4 Data Splitting

The dataset is divided into training, validation, and test sets for model training and validation. Training typically uses 70% of the data, whereas testing uses 15% and validation uses 15%. The splitting ensures that the model is exposed to a diverse range of examples during training while retaining unseen data for evaluation. Techniques for cross-validation can be used to prevent over fitting and increase model reliability. This step ensures the system's ability to generalize effectively across new data and avoid bias from training on similar examples.

4.2.5 Load SVM, KNN for Training

Once the data is pre-processed and split, the next step is to load the machine learning models. Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) are loaded from scikit-learn or similar libraries, which offer straightforward APIs for classification tasks. The hyper parameters are adjusted for optimal performance after the training dataset is used to individually train each model. The models are stored for later use during testing and predictions.

4.2.6 Load Input Image and Check Dataset

After loading the models, an input image (which could be a currency note) is loaded and pre-processed in the same way as the training data (resized, normalized, etc.). The preprocessed image is then passed through the trained model for prediction. Each model (SVM, KNN) performs the task of classifying the image as real or fake. The results are compared against the ground truth to evaluate the model's performance. This step is critical for real-time currency verification, where the system checks whether the input image corresponds to a real or counterfeit note based on the trained classifiers.

IV. RESULTS

The project predicts the currency real or fake based on trained algorithms and after the training process and test the project by giving the input images of real and fake currency notes.

Now, give the input image of real fifty rupees note and the result will be displayed as fifty original.

Fig No 2: Fifty rupees Currency note

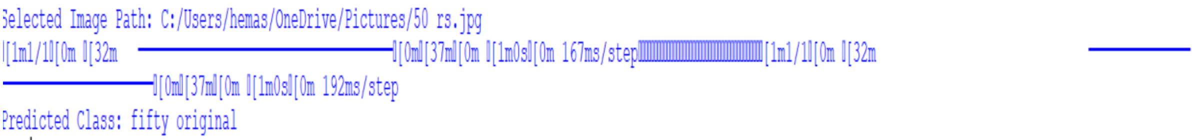

Fig No 3: Detection of currency note

Now take the input as fake five hundred rupees note and the result will be displayed as fake five hundred rupees note.

Fig No 4: Fake five hundred rupees note

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Selected Image Path: C:/Users/hemas/Downloads/Fake Bill Detection Using MHYBRID CNN(VGG16+MOBILE NETV2+LSTM based caption generatorachine Learning/Fake Bill
Detection Using MHYBRID CNN(VGG16+MOBILE NETV2+LSTM based caption generatorachine Learning/test/five hundred fake/500.5.jpg
[1m1/1[0m [32m ━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 162ms/step [1m1/1[0m [32m ━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 198ms/step
Predicted Class: five hundred fake
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Fig No 5: Detected fake currency note

V. CONCLUSION

This project presents a robust solution for rupee recognition and authentication by utilizing feature extraction techniques. The combination of these methods enhances the accuracy of fake currency detection while maintaining low algorithmic complexity compared to other recognition systems.

VI. FUTURE SCOPE

The future scope for fake currency detection is vast and promising. With advances in machine learning, image processing, and AI, systems can become faster, more accurate, and capable of detecting even highly sophisticated counterfeit notes. These technologies can be integrated into ATMs, vending machines, and mobile apps for real-time use. Future systems may also support multiple currencies, learn from new counterfeiting patterns, and be used by banks, retailers, and even individuals to enhance financial security and reduce economic losses due to fake currency.

ACKNOWLEDGMENT

The authors would like to thank Dr. G. Srinivas Rao, Principal of Bapatla Women`s Engineering College, and Mrs. Shaik Shameera, Assistant Professor at Bapatla Women’s Engineering College and our guide, we extend our heartfelt thanks, for their valuable guidance and insights throughout the research for their constant encouragement and institutional support.

We also acknowledge the collaborative efforts of our team members, Chekuri Hema Sri, Kunam Bhanu Sri and Mukku Keerthi Reddy, whose contributions were integral to the successful completion of this work.

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