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Fake-Indian-Currency-Detection with Deep Learning Based-Xception CNN

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Abstract: Counterfeit money is still a major problem for banks and the economy. With the growing complexity of counterfeiters, conventional ways of identifying fake money are less effective. The current research introduces a deep learning-based approach for identifying fake Indian currency notes of ₹100, ₹200, and ₹500 denominations. With the help of the Xception model, which is good at detecting minute image details, the system becomes adept at distinguishing subtle differences between real and fake notes. The model is trained on a data set with images of genuine and counterfeit notes, enabling it to learn intricate patterns and subtle differences that tend to be difficult to spot using the naked eye. Experiments show that the Xception-based model achieve superior classification accuracy and offers an efficient productive solution for high-speed, accurate, and automated counterfeiting detection in real-world scenarios. A range of data such as images of genuine and fake banknotes under various conditions are used in an attempt to enhance the robustness of the model. The proposed system demonstrates high accuracy and reliability, indicating that it can be applied to real-time counterfeit detection systems for enhanced security and confidence in financial transactions.

Keywords: Fake Currency Detection, Xception Model,Deep Learning, Indian Banknotes, Image Classification

I. INTRODUCTION

The Counterfeiting has increased to a highly critical issue, and it's threatening the financial systems as well as the confidence in economic transactions. In India, the issue is most severe in the popularly used denominations like ₹100, ₹200, and ₹500 notes.Even with efforts by the Reserve Bank of India to integrate advanced security features in the currency, counterfeiters find ways to duplicate real notes by increasingly more complex means, thus making traditional methods of detection less effective.Hand-based counterfeit note detection methods such as ultraviolet scanning, watermark verification, and microprint validation are not just time-consuming but also susceptible to human error when high-quality counterfeits are employed. There is, hence, an imperative need for an effective, accurate, and automatic method for detecting counterfeit currency. Deep learning, taking the shape of Convolutional Neural Networks (CNNs), has proved to be very successful in the majority of image-related applications because it can learn high-level features directly from the data. Among the different deep learning architectures, Xception is notable for its exceptional accuracy and efficiency. Developed as an improvement over the Inception framework, the Xception model uses depthwise separable convolutions, enabling it to extract detailed spatial features with reduced computational cost. This makes it highly effective for applications that demand careful distinction of fine details, such as distinguishing between real and counterfeit currency notes. The Xception model exploits transfer learning, using its past training on large-scale image datasets such as ImageNet, and can be fine-tuned quite efficiently using a relatively smaller dataset of currency notes. This work utilizes the Xception architecture to detect fake Indian currency of ₹100, ₹200, and ₹500 denominations, chosen because of their extensive use and the high rate of counterfeiting. Although Indian currency incorporates several layers of security features, counterfeiters often manage to imitate many of them with alarming precision. The system would train on an archive of actual and counterfeit notes imaged at a variety of lighting conditions and angles so the model can acquire the minute texture, color, and watermark positioning variations that characterize legitimate notes compared to counterfeits. After training, the model can effectively predict the genuineness of new, unseen images of currency, providing a strong solution for automated counterfeit note detection. But there are problems to be fixed in developing an effective system. High-quality fakes can mimic the genuine closely, and very difficult to identify. Even the genuine notes show variations caused by aging, decay, or marginal differences in manufacturing, which can confuse the model if not processed carefully. Environmental conditions such as lighting, camera resolution, and angles of photography also affect detection. Additionally, preparing an exhaustive dataset consisting of large samples of duplicate notes is no trivial task but is essential to train a good generalizing model across various circumstances. To break these barriers, the project relies heavily on adequate data collection, preprocessing, and augmentation methods in order to render models robust.

The primary objective of this research is to design a robust and dependable counterfeit currency detection system based on the Xception deep learning model. Major goals are to build a heterogeneous and well-balanced dataset of authentic and forged ₹100, ₹200, and ₹500 banknotes, using advanced preprocessing methods to normalize the input data, optimizing the Xception model to achieve peak classification performance, and testing the system by employing metrics like precision, recall, accuracy, and F1-score. Moreover, the project seeks to develop a practical application that will be implemented in real-world scenarios such as banks, retail shops, and automated teller machines to achieve quicker and more precise currency validation. The organizational work starts with a discussion of the existing literature, followed by an elaborate presentation of the methodology, including creation of the dataset, training the model, and performance assessment.

The results of the experiment are then discussed and compared, and the effectiveness of the model is summarized along with recommendations for future improvement.

II. RELATED WORK

This section provides significant research contributions to the domain of fake currency detection

1) Jakkula Kannamma et.al the technology is based on the identification of fake currency based on the use of the Collapse Processing Method (CNNS). By training the CNN on another dataset using real and fake currency images, the system can accurately identify counterfeit memos by activating automatic pattern recognition. Whereas initial processing and data enlargement enhance model output, graphical representations like confusion matrix and functional cards shed light on model decisions. The study concludes with the aim of developing a user-friendly application for real-time verification of currency within the financial system.
2) M R V Vyshnavi et.al this paper is a complete survey on identification of counterfeit Indian banknotes using some machine learning techniques. Some monitored learning algorithms were KNN, decision tree, SVM, random forest, logistic regression, and naive Bayes. Moreover, explores the performance of LightGBM, which is a gradient boost algorithm, and checked whether it is efficient or not after detection. This research featured extraction attributes and banknote analysis from classification accuracy for all algorithms. The findings revealed that LightGBM surpasses conventional techniques and is more accurate and efficient in the detection of counterfeit notes.
3) Kota Sai Sree et.al This paper introduces an innovative framework that combines deep learning and image processing methods for detecting counterfeit currencies. Employs a hybrid method of recognizing and localizing counterfeit notes by utilizing a combination of Reset50 for functional extraction and generation controversy network (Goose) extraction in order to enhance system performance. This approach enables the creation of images through synthetic forgeries, expands the training set, and enhances the model's robustness for a range of forgery methods. This system exhibits high accuracy, separating real notes from counterfeit currency notes.
4) Boddu Srilatha et.al This paper presents a real-time system based on folding networks (CNNs) to differentiate real currency notes. From the bill image analysis, the system extracts bill features like textures, color histograms, edge patterns, and more to identify the variations that characterize counterfeit currency notes. The methodology showcased in this paper a high level of accuracy in identifying fake notes and offers a robust solution to implement it in different sectors like banking, retail and law enforcements in detecting counterfeit currency.
5) Sai Charan Deep Bandu et.al The system applies image processing and machine learning algorithms to detect counterfeit Indian currency bank notes. The first step is to do with the image form and capture high-resolution photos so as to highlight security features. It then followed by with initial processing step. Gray level conversion and noise have been added for enhanced image quality. The features include to extract focus to recognize key aspects like transparency, safety threads, and microprinting for detecting counterfeit currency notes from real notes
6) Ashok Kumar et.al This paper includes the application of ensemble learning methods to enhance the robustness and accuracy of counterfeit currency detection systems The ensemble learning has the ability to leverage the strength of multiple models to counteract the weakness of single classifiers such as overhauls and sub adaptive agents. Currency image characteristic extraction is done by techniques such as edge detection, color histograms, and texture analysis. The system displays better classification accuracy, indicating the possibility of real-time deployment in safety applications like ATMs and currency enablers.

7) Rajeev Kumar et.al The paper includes extreme learning machines (ELMs) suggest identifying monetary currencies, in a type of hidden neural network. This paper presents a pipeline where the notes images are preprocessed using techniques like gray-level transformation and normalization before being served as an input to the Elm model. This research indicates that ELM currencies can be divided into real or counterfeit but are quicker and less resource intensive than deep learning models, so are an appropriate choice for low latency systems, including mobile apps and kiosk embedded systems.
8) Sai Tarun Kara et.al This paper employs deep folding networks (CNNS) for detecting counterfeit Indian currency. Unlike conventional approaches that need manual functionality extraction, CNNS can learn functionalities like textures, shapes, safety brands, and others directly from the raw image automatically. The author presents CNN models trained on various datasets via photographs of real and counterfeit notes.
9) Aman Bhatia et.al This paper combines machine learning algorithms including Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) with image processing methods. . Extracted functions are passed on to the machine learning model for classification. Using SVM as a classification tool and image processing for feature extraction, the system has the capability to classify grades of currency as real or highly reliable. This paper demonstrates that a blend of such methods enables the detection to be faster and more accurate than lone image processing.
10) Shamika Desai et.al This paper incorporates CNN with a generative, provocative network to identify counterfeit money bills. The CNN framework is structured to learn sophisticated features like photograph serial numbers, watermarks, and color patterns. The GAN model is employed to generate realistic counterfeit samples on which you can further train the CNN. Demonstrate that data expansion technology enhances the performance of CNNs so that better generalization and higher detection accuracy of forged notes can be achieved.
11) Shashank Patel et.al This paper brings out the promise of deep learning models, especially foldable networks (CNNS), in automating counterfeit money detection. The CNN model is trained using this data record to achieve a better accuracy rate than classical machine learning models like Support Vector Machine (SVM) and K-Nearest Neighbor (KNN). This study finds that the deep learning model is appropriate for this task, since intricate patterns can be edited in currency bills.
12) Dr. S. V. Virakamath et.al This paper gives an overview of the different image processing methods employed to detect counterfeit currencies. Cross-checks methods like edge detection, morphological manipulation, texture analysis, and color histogram use. It contrasts conventional methods with newer methods like machine learning and deep learning and illustrates how this discipline has grown over the years. This overview also identifies the advantages and limitations of these methods. This is still image processing techniques like watermark checking and UV-based detection, but more and more dominated by data-driven techniques like CNNS.
13) Kiran Kamble et.al This paper includes the application of deep Convolutional Neural Networks (CNNs) to detect fake currency. A deep CNN architecture to learn features is introduced for feature extraction methods. Utilizes a large dataset of images of real and forged currency notes for processing. The network is also learned to classify the notes using learned patterns including texture, differences in color, and security elements such as watermarks. The CNN model exhibited better accuracy than other machine learning methods, highlighting the power of deep learning to automate counterfeit detection.
14) Akanksha Upadhyaya et.al In this paper, a comprehensive discussion of the different classification methods employed to identify forgery is introduced. In this research, a number of models of machine learning are assessed, including by producing banknotes, employing banknotes to classify banknotes, random forests, SVMs, and neural networks.
15) Sangwook Baek et.al Multi-spectral images capture light on various wavelengths through the visible range. These images reveal hidden features like invisible watermarks and changing color inks. The writer merges data about multispectral images with machine learning models for reducing the false rejection of authentic items and enhancing precision in detecting fakes. Using the spectral reflectivity of banknotes at multiple ligaments, the system is more sensitive to identifying counterfeit notes compared to mere visible-image-based traditional methods.

III. METHODOLOGY

A. Dataset Description

The Indian counterfeit currency detection dataset contains images of ₹100, ₹200, and ₹500 denomination banknotes, both genuine and fake. Images were taken with different lighting conditions, angles, and backgrounds to provide diversity and enhance the model's generalization capability. Each image was accurately marked as 'authentic' or 'fake' to facilitate supervised learning when training models. Preprocessing operations of resizing, normalization, and noise removal were utilized for quality and consistency checks.

Data augmentation operations of rotation, flipping, and adjustment of brightness were applied as well to enhance the dataset and enable generalization of the model. This very well-balanced diversified dataset is utilized as the basis for training and testing of the Xception-based system for detecting counterfeit currency.

B. Model Development and AI Techniques

The Indian Currency notes are utilized as dataset for research work.

1) *Preprocessing:* In machine learning, and especially in computer vision applications, the quality and uniformity of input data greatly influence the performance of models. Preprocessing in this project was an essential step in preconditioning both the training and real-time input images for fake currency recognition. The preprocessing pipeline was also designed with utmost care to make sure that the data input into the deep learning models was clean, standardized, and could represent a wide range of real-world situations.This part of the text explains the step-by-step procedure followed during the preprocessing stage, such as image standardization, augmentation techniques, normalization, label encoding, and webcam data preparation in real time.
2) *Image Collection and Standardization:* The first step in preprocessing was to gather high-resolution images of ₹100, ₹200, and ₹500 Indian banknotes. The dataset contained both authentic and fake samples so that the model trained to recognize minute differences between real and fake notes. All gathered images were made to undergo an equal resizing operation, wherein all images were resized to 299×299 pixels. This was the size chosen because the Xception model, the feature extractor in use, accepts inputs of this specific size. Sizing all images equally aside from maintaining compatibility with the model architecture, also reduced computational strain upon training and prediction. In addition, all images were converted to three-channel RGB format regardless of whether the original images were grayscale or not, to maintain consistency with the expected input format of the pre-trained model.
3) *Data Augmentation for Training:* To enhance the model's generalization ability and avoid the overfitting, numerous data augmentation techniques were used throughout training. Data augmentation was able to augment the training data artificially by including random transformations and thereby enable the model to learn better variations of orientation, illumination, and partial occlusion. Some of the methods employed included random rotations of up to 30 degrees to enable the model to identify currency notes even when not aligned precisely. Horizontal and vertical translations, moving images by a maximum of 20% of their size, enabled the model to accommodate situations where notes were shown to be off-center.Shear operations were incorporated to mimic situations when photos were being taken at some angle rather than overhead. To add, randomized zooming procedures, including zoom-in and zoom-out adjustments, trained the model to identify notes of varying proximity. The horizontal flipping was also applied at random; in spite of the fact that real currency notes have a certain orientation, this behavior compelled the model to attend to prominent intrinsic features rather than relying on positional information. Wherever these augmentations provided fill-in for void regions in the images, the 'closest' fill mode replaced missing pixels with nearby valid ones in an attempt to maintain visual continuity. Through the employment of this suite of augmentation strategies, training data replicated a large variety of real-scenario environments and thus significantly augmented the generalization capability of the model to novel cases.
4) *Normalization:* Once data augmentation was completed, all the images were normalized to have optimal performance of the deep learning model. The raw pixel intensity levels were between 0 and 255; they were normalized between 0 and 1 by dividing every value by 255.Normalization played a critical role in reducing computational complexity, achieving faster and stable convergence during the training process, and rectifying issues such as exploding and vanishing gradients. Through offering a normalized distribution of the input data, normalization heightened the efficacy of learning and also promoted overall prediction accuracy and reliability within the model.

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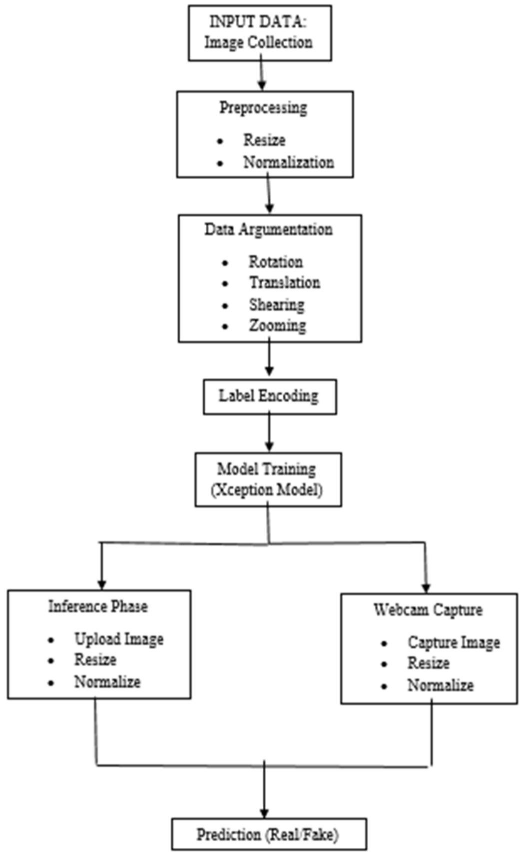


Flow chart

5) *Webcam Image Preprocessing:* The software incorporated functionality for real-time image capture from the device's webcam, which needed to be processed in real time to meet the input requirements of the trained model. When a user clicked on an image from the webcam, it was initially read into the system via OpenCV. The image was resized to 299×299 pixels to meet the dimensions expected by the model. After resizing, pixel values were normalized to the range 0–1 to be consistent with training data of the model. The color channels remained in RGB form since converting them to grayscale may adversely affect the performance of the model. Unlike training images, images captured using a webcam did not receive any augmentation during inference. Maintaining the original form of the captured image enabled the model to make more precise predictions from actual inputs.
6) *Label Encoding:* To efficiently deal with the task of classifying banknotes into real or counterfeit, a binary label encoding method was used. Real notes were labeled with 1, while fake ones were labeled with 0. The dataset was loaded and organized using TensorFlow's flow_from_directory function, where class_mode was clearly specified as 'binary' to accommodate this two-class scenario. Using binary labels not only simplified the training process but also improved the efficiency of model testing. In addition, this binary framework enabled the last layer of the model to be a single output neuron with a sigmoid activation function, which reduced the overall network design and increased prediction accuracy. This approach offered a tidy and efficient means to address the problem of classification with minimal data-handling and model-configuration complexity.
7) *Preprocessing During Inference:* Even though data augmentation was crucial in the model training stage, it was deliberately left out at inference time. At prediction time, every image uploaded or taken was resized to the specified dimensions and normalized only. Nothing else was done, leaving the original features of the input intact. When several images were submitted, they were processed sequentially, and each image was treated with the same standard preprocessing routine prior to being fed into the model. The repetitive and low-variable preprocessing in inference served to preserve the high accuracy of the model and avoided the introduction of undue variability that might jeopardize prediction stability.

IV. RESULT

The proposed system was implemented as a web-based application capable of detecting counterfeit Indian currency notes and performing real-time currency conversions. A series of experimental tests were conducted to evaluate its performance, accuracy, and usability across different functionalities. This section presents and discusses the observed results from six primary testing scenarios.

A. Main Dashboard Interface

Figure 1 displays the primary dashboard of the application.

The dashboard serves as the central navigation point, enabling users to access all core functionalities of the system, including counterfeit currency detection, informational modules on currency features, and a real-time currency conversion tool. Each feature is represented through a clearly labeled interactive card, providing a clean and intuitive user experience. The interface utilizes a minimalist design with gradient backgrounds and structured layouts to ensure ease of use. This design approach allows both technical and non-technical users to engage with the application seamlessly, improving overall accessibility and usability.

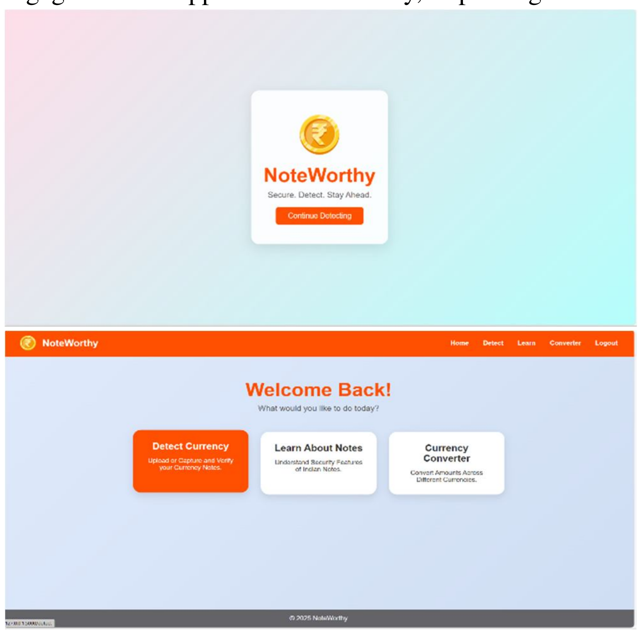


Figure 1: Dashboard interface showing navigation options for detection, learning, and conversion features.

B. Detection of Fake ₹500 Note Using File Upload

Figure 2 illustrates the outcome of uploading a counterfeit ₹500 note through the system's file upload interface.

The detection mechanism leverages a convolutional neural network based on the Xception architecture. Once the image is uploaded, it undergoes preprocessing including resizing, normalization, and color space conversion. The model then performs classification to determine whether the note is genuine or counterfeit. In this scenario, the system successfully identified the uploaded note as fake, confirming the robustness of the model in identifying forged currency features. The prediction was generated within approximately two seconds.

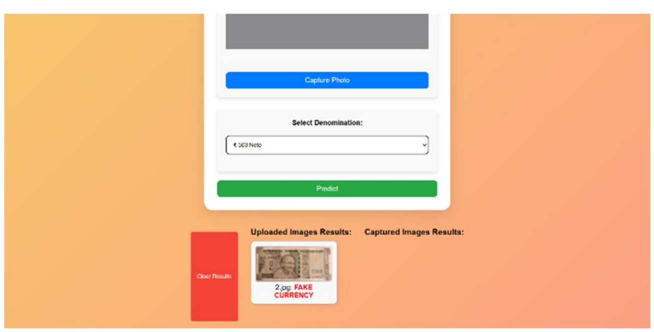


Figure 2: Detection result for a counterfeit ₹500 note uploaded via file input interface.

C. Detection of Real ₹100 Note Using File Upload

Figure 3, a real ₹100 note was uploaded to test the model's recognition of authentic currency.The model accurately predicted the note as real, validating its ability to distinguish between authentic and forged notes. This reinforces the system's reliability in identifying key visual features, such as watermarks, latent images, and microtext, which are typically embedded in real currency. The detection process was quick, and the output was displayed with high clarity in a user-friendly format.

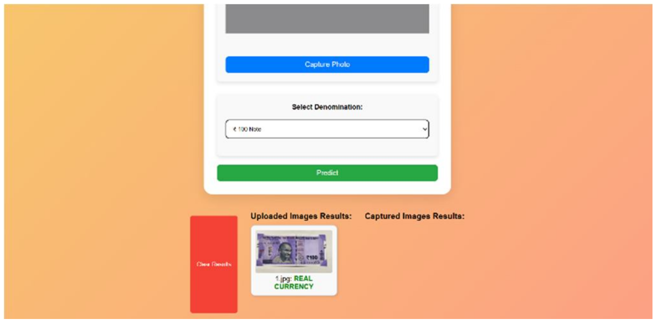


Figure 3: Detection result for a genuine ₹100 note uploaded through the system.

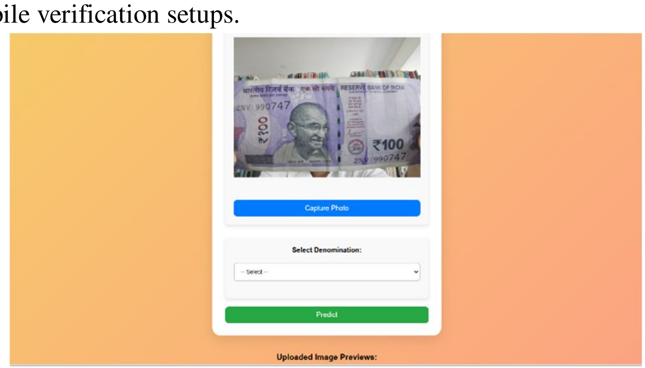
D. Batch Detection via Multiple Image Uploads

Figure 4 demonstrates the system's ability to process multiple uploaded images in a single session. To test scalability and efficiency, a set of both real and fake currency note images across multiple denominations were uploaded simultaneously. The system handled the batch input by processing each image independently in a looped inference pipeline. Each prediction was rendered separately below the upload section, with appropriate labeling. This functionality is particularly useful for institutions or users who need to verify multiple notes efficiently, such as banks, retail chains, or currency sorting centers. The interface-maintained responsiveness despite the increased input volume.

Figure 4: Multiple note detection with simultaneous upload of real and fake currency images

E. Real-Time Detection Using Webcam Capture

Figure 5 highlights the system's capability to detect currency notes via live webcam input. In this scenario, a physical note was captured in real-time using a webcam connected to the application. The captured frame was immediately processed by the backend model to generate a prediction. The result was shown beneath the webcam feed interface without the need for manual refresh or redirection. This feature significantly enhances the usability of the system in scenarios where image upload is not practical, such as real-time public checkpoints or mobile verification setups.



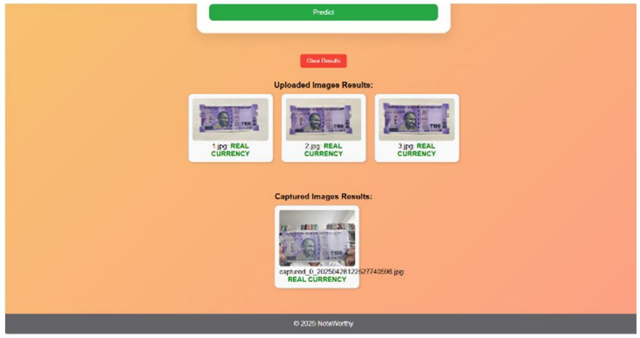


Figure 5: Real-time currency verification using webcam capture and live prediction output.

F. Live Currency Conversion Interface

Figure 6 shows the application's integrated currency converter in action. The currency converter allows users to select from over 150 international currencies using a searchable dropdown interface. Upon entering the amount, the system automatically retrieves and applies the latest exchange rate using a local currency conversion utility. The result is dynamically updated without requiring form submission, providing a smooth and immediate user experience. Additionally, a reverse conversion button is available, enabling users to switch between base and target currencies instantly. This feature demonstrates a strong emphasis on user-centric design and performance optimization.

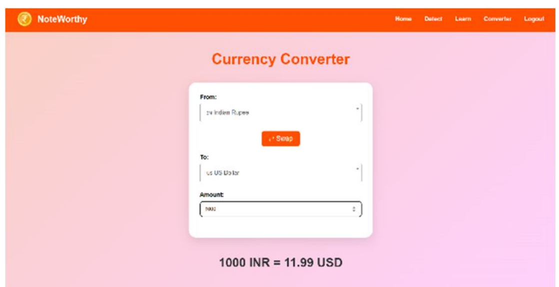


Figure 6: Currency converter interface showing live rate conversion and swap functionality.

V. CONCLUSION

This project shows what powerful image processing methods can do in extracting significant features from the currency bills and facilitating correct differentiation between real and counterfeit bills. With folding networks (CNNS), the system significantly enhances the accuracy of classification and is a trustable method of practical deployment. Due to the feature extraction coupled with deep learning methods the project offers an effective solution to the present problems of currency forgery. In addition, the model performance indicates that AI-driven solutions are capable of substantially enhancing the accuracy and speed of counterfeit detection compared to conventional manual processes with low accuracy and timeliness. The combination of strong trait extraction and deep learning techniques presents an overwhelming solution to the ramp-stretching problem of currency tampering. This technology can significantly utilize usage from financial institutions who want to make automation and cash processing more efficient to combat cases with fake currencies. Additionally, implementing solutions on mobile devices allows checking on the go, making daily transactions more accessible and usable.

VI. FUTURE SCOPE

To diversify the system, the future enhancements can extend support for the broader scope of currency confessions to provide extensive coverage of all kinds of notes. Secondly, the size and diversity of training data boosts the accuracy and resilience of the model so that it can perform optimally under diverse real conditions like various lighting, positions, and wear on the notes. In addition, expanding the dataset to international money could possibly make this system a worldwide solution for identifying counterfeit scenarios. With the integration of optical character detection (OCR), the system can verify the serial number of the money bills and provide further layers of authentication. Offering cloud-based solutions as a service can enhance ease of access and scalability, thus making it accessible to businesses, financial institutions and individuals globally. This not only enhances the performance of the system but also invites constant updates and enhancements without end users, and applications are updated continuously.

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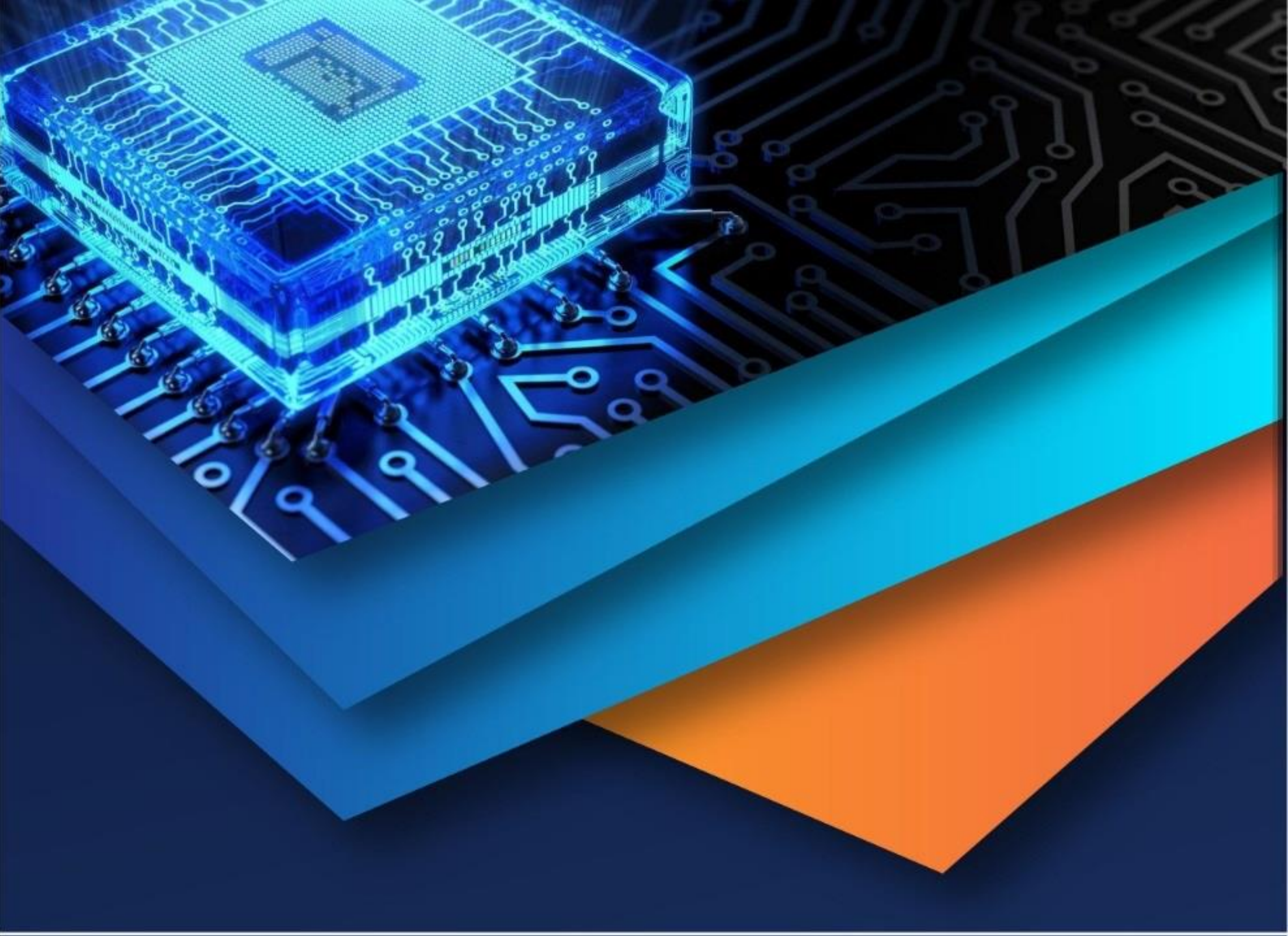

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