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Automated Detection of Counterfeit Indian Currency by Xception CNN and Edge Image Capture with ESP32

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Abstract

This paper explores the application of machine learning (ML) in detecting counterfeit Indian currency using the Xception deep learning model, which analyzes images to distinguish genuine notes from fake ones. Out of the entire dataset, 70% fuelled the training phase, 20% guided validation, and the final 10% was reserved for testing to evaluate the model's performance comprehensively. Performance assessment relied on indicators like correctness and specificity to measure how well the model did. The Xception model achieved an impressive 99% accuracy during training but showed limitations in validation, performing at only 10%. These challenges highlight issues like dataset imbalance and the need for effective feature extraction to enhance reliability. The findings underline the potential of ML in aiding banks and law enforcement agencies in identifying counterfeit currency efficiently. However, the study also identifies key areas for improvement, including addressing data imbalances and refining the model to improve validation effectiveness. Next-stage exploration will focus on enhancing the model's robustness, incorporating additional features, and transitioning the model toward real-world applications.

This research demonstrates the promise of ML in tackling the growing problem of counterfeit currency and sets a foundation for further advancements in this domain.

Introduction

Fake money remains a big problem putting the financial health of countries at risk and making people lose faith in how money works. When counterfeit Indian cash moves around, it doesn't just hurt the economy's honesty - it also helps bad things happen like cleaning dirty money, funding terrorists, and dodging taxes [1]. As those who make fake bills keep getting better at it, the old ways of spotting fakes often can't keep up with this growing issue.

In past, people spotted fake money by looking at it using UV lights, or fancy machines that checked special security features like watermarks tiny writing, and holograms. But these ways took a lot of work needed trained staff, and couldn't handle large amounts [2]. Also, this equipment isn't always easy to get in country or far-off places where fake money can hurt the economy even more. The latest breakthroughs in machine learning (ML) and computer vision give us a promising new way to spot fake money. These cutting-edge systems use neural networks to examine intricate patterns, text details, and visual elements on banknotes. They're more accurate and work faster than the old methods [3]. By mixing insights from data with the ability to roll out on a large scale, ML models can boost our ability to catch counterfeit cash.

This research presents a strong and expandable system to spot fake Indian money using the Xception deep learning model. This model is known to work well in sorting images. The data used in this study has both real and fake currency notes processed beforehand to make important features stand out. The researchers split the data into three parts: 70% to train the model, 20% to check its progress, and 10% to test how well it works. They used measures like accuracy, precision, and recall to see how good their approach is.The team tackled major hurdles like uneven class distribution and feature selection. They used data boosting and fine-tuning methods to make sure the model works well in many different situations. The first round of tests showed the training was very accurate (99%), but they still need to work on making the validation more precise and the whole system more stable. The research also points out real- world uses such as putting the system in ATMs, at bank tellers, and in phone apps to spot fake money right away [4].

The rest of this paper goes into depth about other studies on this topic, explains how they did their work, walks through how they put it

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all together, and talks about what they found. At the end, they look at what could come next how to make the system more accurate easier to understand, and more likely to work well in actual use.

Literature review

Devid Kumar and Surendra Singh Chauhan (2024) discussed how counterfeit currency detection has evolved with the use of image processing and machine learning. Methods such as feature extraction, edge detection, and classification with SVM and CNN have shown to be effective in examining security features. Additionally, real-time mobile applications that utilize computer vision offer accessible and precise solutions for identifying counterfeit currency notes.[5]

Aneena Babu and Vineetha Shankar P (2024) carried out a comprehensive study on detecting counterfeit currency, employing advanced image processing techniques, machine learning methods work with hybrid models to reach better accuracy of identifying fake notes. They found that key methods like ORB, SSIM, and deep learning significantly enhanced performance. However, they also noted challenges such as limitations in datasets, the need for real-time processing, and the ever-evolving nature of counterfeiting techniques. The study highlights the importance of developing advanced algorithms, integrating blockchain technology, and fostering international collaboration to create scalable and effective systems. These insights emphasize the vital role of technology in the global fight against counterfeit currency.[6]

Neha Sharma and her team (2018) studied how well existing CNN architectures work for real-time object recognition in video feeds. Widely used CNNs for object detection and classification from images include AlexNet, Xception, and ResNet50. There are various image datasets used to measure the efficiency of different architectures of CNNs. Common benchmark datasets for evaluating CNN performance include the ImageNet dataset, as well as CIFAR10, CIFAR100, and MNIST. This work conducts a detailed assessment of three prominent network architectures: AlexNet, Xception, and ResNet50. The research utilizes the three most popular datasets—ImageNet, CIFAR10, and CIFAR100—because testing a network's performance on a single dataset does not provide a complete picture of its capabilities and limitations. An important distinction is that videos were not included in training, they were used only for evaluation. It was noted that Xception and ResNet50 demonstrate superior object recognition precision compared to AlexNet.[7]

Karan Chauhan and his colleagues (2018) describe deep learning as a computational method inspired by how the human brain works. This approach uses interconnected layers of artificial neurons to process large datasets. These neurons can identify hidden patterns without any explicit human help. This ability allows deep learning to work with unstructured data formats, such as images, audio, video, and text. Among the different architectures, convolutional neural networks (CNNs) have become well-known as one of the most effective techniques for analysing visual information. A deep learning convolutional network built using Keras and TensorFlow is implemented in with Python, CNNs can easily tell the difference between two image categories. When used together, the ReLU activation and sigmoid classifier generated the best results, outperforming all other combinations tested.[8]

Gouri Sanjay et al. (2018), Faking counterfeiters thus become difficult in recognition by deployment of new technology. Best means to prevent fraudulent duplication might probably remain counterfeit detection software, which is easily available and very realistic. This will grant us the ability to recognize Indian currency using a webcam in real-time. This project bears background in image processing technology, applied for checking the valid currency notes. The software checks currency for fakeness based on the extraction of specifications of notes. Software implementation success is measured by two key factors: correctness and speed. Primarily, it is seen as working on those parameters that will not be understandable for counterfeit notes. Therefore, we fall back on working on minutiae parameters which shall take care of differentiation distinguishing counterfeit from genuine notes.[9]

Shital Mahajan and the research team (2018), "Survey paper records compilation of various article regarding paper currency counterfeiting recognition and detection systems; attempts to present a survey on fake money detection because almost every country facing in the world is hit by the problem of forged money; in India, the maximum extent of this evil incorporates itself into the country." There have been no previous surveys on methodologies regarding currency identification about these and useful measures to develop and analyze new approaches and algorithms with good performance are given in the full survey presented here.[10] Technologies that are considered almost impossible are being discussed extremely seriously. Sumeet Shahani et al. (2018) proposed the use of machine learning approach for evaluating the verification of bank notes. In this process, some labelled-input training algorithms, such as Back propagation Neural Network (BPN), and Support Vector Machine (SVM), have been applied to differentiate between authentic bank notes and the fakes. The study further presents the comparative study of these algorithms applied in bank note classification.[11]

References are going to be made by "Sehla Loussaief in 2018 along with co-authors focused on image classification. The main challenge in image categorization is features extraction and how images are represented as vectors. We present the Bag of Features approach used to create an image representation. The classification accuracy of various algorithmic classifiers is tested against a standard based on images from the Caltech 101 dataset. In the process of extracting features, we compare the traditional Speeded- Up Robust Features (SURF) method with global color-based feature extraction methods. This study aims to find the most effective machine learning framework for accurately recognizing stop sign images. [12]

Sandeep Kumar along with co-authors Objective acknowledgment describes the new science of the computer vision. Not least of the tasks in computer-based visual processing, most complex and demanding fields. Numerous methods have been found for this. An entirely new model introduced for a very accelerated although highly stable approach. A comparison was done with the Easynet model with other many architectures also. At the test time the Easynet model encompasses the whole image as it actually takes global context into account to inform predictions. At the time of prediction, the present architecture constructs confidence scores for assigning an object to a specific class. Inference is performed using one unified network evaluation. Now the problem of object detection is regression into space-separated bounding boxes and associated class probabilities.[13]

Rinku Nemade et al.(2017), linked the art oils in order to prize from machine literacy. presently forged oils are linked in the galleries with the examination of oil with an art expert. Research in the field of work for automated cultural identification is veritably small. The thing is to determine whether two oils are painted by the same person by using machine literacy. In our opinion, the results that we're working on for discovery of phony in art oils contain fascinating operations for janitors and chroniclers of art. Machine learning helps the system identify the relationships between artists. It does this by looking at the unique traits and styles found in their oil paintings. [14]

Tianmei Guo and co-authors 2017, it was observed to be applied to deep literacy in the picture bracket, sample shadowing, orientation assessment, textbook discovery and identification, perceptual importance discovery, activity analysis, semantic segmentation. bus latent space generator, meager algorithm design, confined Models such as Boltzmann Machines, DBNs, and CNNs are employed are the most common deep literacy models. Among the different architectures, feature-extracting neural networks show peak performance in sample bracket. An innovative simple CNN model has been created for image bracket. This basic deep feature network processed the visual dataset. This network served as a foundation. Different types of the dataset were analyzed. Multiple tuning methods were applied to see how parameter optimization affected the performance of visual classification. [15].

Antre, Kalbhor, Jagdale, Dhanne, and Prof. Onawane(2023) conducted a study on fake currency discovery applying deep feature Networks, a subset of deep literacy ways. The authors aimed to tackle pressing problem of fake currency, leading to a considerable trouble for the frugality. Team developed one robust system able of distinguishing between genuine and fake Indian rupee notes. The experimenters constructed a comprehensive dataset comprising images of authentic and fake notes captured under colorful conditions, icing the model's rigidity to real- world scripts. The CNN architecture learned and validated from the information set, completing model optimization delicacy of 97.72 and validation delicacy with 92.31. Such results emphasize high delicacy and trustability of the model in relating fake currency. The study highlights the implicit operations of such a system in banks, fiscal institutions, and businesses that manage cash deals, where it could effectively reduce fiscal losses caused by fake notes. The authors' donation demonstrates the efficacity of CNNs in addressing profitable challenges related to fake currency, paving the way for unborn developments in automated currency confirmation systems.[16]

Kumar and Chauhan(2020) proposed a computer vision-grounded methodology for detecting fake Indian paper currency. The approach focuses on point birth and dataset development to enhance the delicacy of currency discovery. The authors employed the sphere(acquainted FAST and Rotated BRIEF) algorithm combined with the Brute- Force matcher for point birth and matching, which proved to be effective in relating identifying characteristics of genuine and fake bills. The system demonstrated an average delicacy of over to 95.0 when tested across colorful appellations of Indian currency. This study highlights the eventuality of computer vision ways in addressing the challenges posed by fake currency. The authors' work provides a foundation for farther advancements in automated currency authentication systems, particularly in fiscal institutions and businesses handling substantial cash deals.[17]

Antre, Kalbhor, Jagdale, Dhanne, and Prof. Sonawane(2023) addressed the profitable trouble posed by fake currency through a system applying deep feature network for directly determine real and counterfeit notes. Specific recommend way operates in real- time, assaying images of currency notes to determine their authenticity. The study involved creating a dataset with images of genuine and fake currency notes across colorful appellations for training and testing purposes. The CNN armature employed comported belonging to deep feature layers for point birth, maximum- subsampling layer for dimensionality reduction, and a final affair subcaste delivering the probability of a note being authentic or fake. The architecture get a correctness delicacy with 97.72 along with testing delicacy with 92.31, demonstrating its trustability and robustness in fake discovery tasks. Despite its advantages, the study faced challenges similar as a limited dataset size and high original perpetration costs. nevertheless, the exploration highlights the implicit operation of CNN- grounded systems in real- time scripts, particularly in fiscal institutions and businesses, offering an effective tool to alleviate the pitfalls associated with fake currency.[18]

Suneetha, Meenakshi, Maruthi, Lakshmi Deepak, and Venkata Mani Manas(2023) proposed a real- time fake currency discovery system exercising Convolutional Neural Networks(CNNs). Feting the profitable trouble posed by fake notes, particularly in India, the authors developed a cost-effective fashion to descry fake currency by assaying critical security features similar as watermarks, idle images, and security vestments. The proposed system emphasizes real- time discovery capabilities, making it accessible and practical for wide use. It achieved a delicacy of 80, demonstrating its eventuality for operations in colorful sectors, including banks and retail businesses. The cost- effectiveness of the system further enhances its usability, particularly in resource- constrained surroundings. still, the study conceded challenges, particularly in achieving advanced delicacy, which could impact the trustability of the discovery system. Despite this limitation, the exploration provides a precious donation toward the development of accessible and affordable fake currency discovery systems, addressing a critical profitable issue.[19]

Nikita Bhatt et al.(2017), deep neural networks have conquered exploration area in machine literacy and pattern recognition. Complex literacy is a computing model which independently obtains layered feature representations in multi-level neural networks infrastructures dedicated to bracket. Specific thing intended to uncover important features using deep learning networks. In the period with large-scale data, suitable for any practical application operation, big quantum the data should be processed reused, complex literacy outperforms other current computational learning techniques.[20]

Ryutaro Kitagawa and other tea member in 2017 automated system for organizing sorting system setup without manual input descry pictures in the data subset bills, for enabling be snappily stationed within a new geographical area. habituated deep feature Networks to descry pictures into fully newly prepared groups of the system is built to recognize bills accurately, even with differences in how they appear. This includes variations in size and lighting conditions, much like how facial exposure can change.[21]

Achal Kamble and co-authors (2018) developed a technique to identify counterfeit Indian notes by encoding each note into a multidimensional space that reflects its variations compared to reference images. Each dimension represents how the note differs from a standard prototype. To find differences between two currency images, important feature points are first identified and described. Then, these points are paired based on the qualities of the notes, and unmatched points are removed in a follow-up step. Because counterfeit notes are rare in real life, the SVM classifier is trained only on authentic currency to spot fakes. By using digital image processing, this method provides accurate currency analysis while cutting costs and processing time compared to traditional methods. MATLAB Software is used for this analysis. Day by day exploration work is adding in this field and colorful image processing ways are enforced in order to get more accurate results. The proposed system is worked effectively for rooting extracted features from Indian note images. Key features taken from a currency image are used to identify its value and verify its authenticity. [22]

Research methodology

The proposed model is designed to effectively identify counterfeit Indian currency notes by utilizing advanced computational image analysis methods, along with data-driven learning techniques. This system focuses on detecting fake currency through various security features and visual characteristics, offering a thorough solution for real-time counterfeit detection. The model follows several stages, beginning with data extraction and cleaning, then training and evaluation as shown in Diagram 1. Below is a detailed outline of the Fake Indian Currency Detection system:

Model Workflow

Dataset Loading and Initial Inspection

The process starts with loading a labeled dataset that includes images of both genuine and counterfeit Indian currency notes. This dataset features high-resolution images of real and fake notes as shown in Diagram 2 and Diagram 3. During the initial inspection, an overview of the dataset's structure is conducted, highlighting key attributes such as the image data and its corresponding label (genuine or fake). Ensuring the robustness and range of the dataset is vital in order to the model to learn effectively from various currency notes under different conditions.

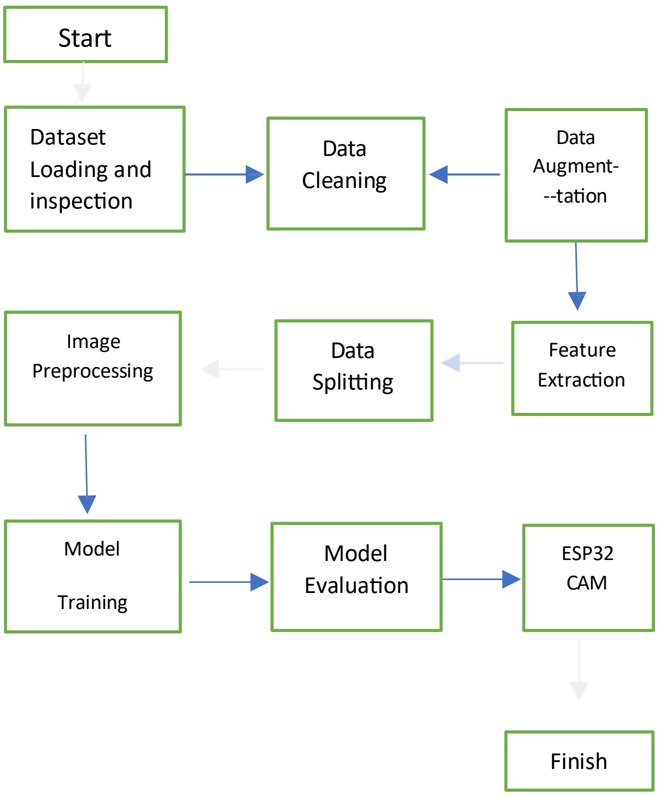

***Diagram 1.** Workflow of the Model*

***Diagram 2.** Legitimate Indian banknote dataset*

***Diagram 3.** Fraudulent Indian banknote dataset*

Data Cleaning

Data Cleaning is an essential step to maintain the integrity of the dataset. This process includes: Removing any corrupted or incomplete images that could introduce noise. Eliminating unnecessary columns or features that do not aid in the classification task. Addressing missing or erroneous entries by either drooping or imputing data. Identifying and removing duplicates to ensure a unique set of training images.

Data Augmentation

To address potential class imbalances in the dataset (i.e., the number of fake notes is lower than real notes), data augmentation is applied. This involves generating synthetic images through transformations such as: Rotation: Rotating images by a random angle to simulate various viewing conditions.

Flipping

Horizontal or vertical flips to introduce variety in the dataset. Scaling: Zooming in or out to create different resolutions of currency images. Brightness/Contrast Adjustment: Modifying the lighting conditions under which currency notes might appear. Cropping: Random cropping to emphasize different regions of the currency notes. These techniques help balance the dataset and make the model more resilient to variations in real-world scenarios.

Feature Extraction

Feature extraction is an essential process where key security elements of the currency notes are extracted and analyzed. These features include: Watermarks: Subtle patterns embedded in the currency that are difficult to replicate. Security Threads: Embedded metallic threads that are visible when viewed under specific lighting conditions. Micro-lettering: Small text or symbols on the currency that are visible under magnification. Color Patterns: Unique colour combinations that are difficult to reproduce in counterfeit notes. Texture Features: Patterns and textures unique to genuine currency notes, analyzed using texture-based algorithms like Local Binary Patterns (LBP)

Dataset Breakdown

For model evaluation, the dataset is split into training, validation, and testing subsets, typically organized as follows: Training partition: 70% derived from the dataset is allocated for guiding the model's learning. Dataset for hyperparameter validation: 20% is set aside for validating the model during the training process. Testing Set: 10% is used for the final analysis to examine the model's capability on data it hasn't encountered. This framework offers a transparent way to test the model's generalization to unfamiliar samples.

Preprocessing for Image

Analysis Images go through several preprocessing steps to standardize them for input into the model: Resizing: All images are resized to a uniform dimension (e.g., 299x299 pixels) to align with the input size required by the machine learning models. Normalization: Pixel values are adjusted to a range between 0 and 1 to facilitate more efficient learning by the model. Noise Reduction: Techniques like Gaussian blur are applied to minimize background noise and emphasize important features. Edge Detection: Methods such as the Canny edge detector are utilized to pinpoint the edges of the currency note and enhance critical features like watermarks and security threads.

Training Phase

Different supervised and deep learning algorithms are trained to identify counterfeit currency: Convolutional Neural Networks (CNNs): CNNs are used to automatically learn intricate patterns from the image data, employing layers of convolutions, activations, and pooling to collect informative traits from currency pictures.

Xception Model

This deep learning model is based on depthwise separable convolutions and is specifically fine-tuned for detecting features in currency images. These models are trained with an optimizer like sigmoid, along with a learning rate scheduler to ensure effective convergence. The training process involves multiple epochs to refine weights and biases for precise classification

Verification of model outcomes

After the training phase, we measure how well the model works using different evaluation criteria:

- **Accuracy:** Measures the percentage of correctly classified images.
- **Precision and Recall:** Evaluates how well the model identifies fake notes (precision) and how well it detects all fake notes (recall).
- **F1-Score:** The combined harmonic measure of precision and recall makes sure we have a fair performance metric.
- **Confusion Matrix:** A confusion matrix clearly shows how accurate the model is by displaying true and false predictions for each class.

Overfitting and underfitting are checked by comparing the performance examining the model on its training and validation inputs

ESP32-CAM Integration:

1. Capture Image (ESP32-CAM): The ESP32-CAM captures an image of the currency note.
2. Preprocess Image (ESP32 or Backend): If necessary, the ESP32-CAM performs basic preprocessing (resize, enhance contrast, etc.). Or, it directly sends the image for advanced processing.
3. Send Image to Backend Server (Wi-Fi): The ESP32-CAM transmits the image to a backend server or cloud for advanced analysis.
4. Model Analysis (Backend): The backend system applies a trained machine learning model (e.g., CNN, Xception) to classify the image as real or fake.
5. Return Result (Backend to ESP32- CAM): The backend sends the classification result (real or fake) to the ESP32-CAM.
6. Display Result (ESP32-CAM): The result is displayed on the ESP32- CAM's interface or used to trigger an alert.

Deep Learning Model Workflow

Xception Model

The Xception model, known for its efficiency in image classification tasks, is employed for counterfeit currency detection. The architecture of Xception consists of:

- **Input Layer:** Accepts the pre- processed and resized currency images.
- **Convolutional Layers:** Extract key features such as textures, edges, and patterns that are indicative of genuine currency.
- **Hierarchical separable convolution:** The defining mechanism of the Xception network, helping to improve performance while reducing computational cost.
- **Fully Connected Layers:** Use the extracted features to categorize the images as authentic or counterfeit.
- **Output Layer:** Provides the final prediction, outputting the probability of an image being genuine or counterfeit.

The Xception model is fine-tuned using a Binary cross-entropy loss function and the Sigmoid optimizer. A transfer learning approach is used by initializing the model with pretrained weights, enhancing learning efficiency, especially with limited data.

Key Contributions of the Proposed Model

- **Data Augmentation and Preprocessing:** These techniques help overcome class imbalances and improve model robustness against varied real-world conditions.
- **Advanced Feature Extraction:** By focusing on unique security features such as watermarks, threads, and micro-lettering, the model is capable of distinguishing counterfeit notes effectively.
- **Multiple Model Comparisons:** The model provides insights into the strengths of various classifiers, aiding in selecting the most efficient approach.
- **Scalability and Instant Application:** The system enables be scalable and deployable in various real-world environments, such as ATMs, mobile applications, and bank verification systems.

Implementation

The following is the implementation process for the proposed framework in the Fake Indian Currency Detection project. This framework outlines steps from dataset preparation to model deployment.

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Dataset Overview

The dataset used in this design is a collection of images of Indian currency notes, both real and fake. The dataset is split into separate folders, one for real currency and one for fake currency, and is used to fit machine learning models to detect counterfeit currency.

- **Dataset Preparation:** The dataset is organized into two folders, one for real currency images and one for fake currency images. The dataset is initially loaded into memory, and initial data refinement is applied to prepare the images for model training.
- **Data Exploration:** The dataset consists of images with labels determining the authenticity of the currency. A visualization of the distribution of real and fake currency images is displayed, giving insight into the dataset's balance.

Data Preprocessing

- **Data Cleaning:** Images are loaded from the dataset, and any irrelevant or corrupted files are removed. Any missing data or images that cannot be processed are handled by ensuring ensuring the dataset includes only authentic images of genuine and counterfeit currency.
- **Resizing Images:** All images are changed to a standard resolution. (like, 299x299) to make them compatible with the machine learning model. Image data augmentation is applied to increase dataset size and introduce variability to prevent overfitting, including transformations like rotation, zoom, flipping, and shifting as shown in Diagram 4.
- **Normalization:** Image pixel values are normalized to the range [0, 1] normalizing by 255 so that the model can process the data effectively.
- **Data Splitting:** The dataset is segmented into training, validation, and testing subsets—for instance, 70% for training, 20% for validation, and 10% for testing—to assess the model's effectiveness. The train_test_split() function from Scikit-learn is employed to partition the data, ensuring a random distribution while preserving the balance between authentic and counterfeit currency images.

Model Training and Evaluation

1. **Model Selection:** Various machine learning models are trained to detect fake Indian currency, including Convolutional Neural Networks (CNN) and pre-trained models like Xception, ResNet, along with EfficientNet. These architectures are known for their high performance in image bracket tasks.. There are many features are extracted by Xception Model like edge, Texture, hologram, ink etc, it is Block14_sepconv1 deep separable Convolution Layer that extract main features and classify whether currency is fake or real as Shown in Diagram 5, Diagram 6 and Diagram 7h.
2. **Model Architecture:** A deep learning model is constructed using CNN layers or pre-trained models, followed by fully connected layers. The last layer is a binary classification output layer, where the two classes are "real" and "fake." The model is shown in Diagram 8
3. **Model Development:** The models are fitted to the training dataset using an appropriate optimizer, like the sigmoid optimizer, and a corresponding loss function, such as binary cross-entropy. To improve model generalization and reduce overfitting, regularization methods, including dropout and batch normalization, are included during training.
4. **Model assessment:** The models are evaluated based on accuracy, precision, recall, F1-score, and confusion matrix. The confusion matrix demonstrates misclassifications, allowing the architecture to be fine-tuned to reduce errors as shown in Diagram 9.
5. **Model Optimization:** Hyperparameter optimization is carried out to enhance the model's performance by adjusting parameters such as learning rate, batch size, and the number of training epochs. Additionally, advanced strategies like transfer learning with pre-trained architectures (e.g., Xception) can be employed to further improve accuracy and reduce training time.
6. **Final Model Selection:** The model with the highest accuracy and lowest error on the validation set is selected for deployment. The selected model is saved for later use in practical applications.

Deployment

- **Model Saving:** The model weights and architecture are saved in a file. (e.g., model.keras) for later use. This model

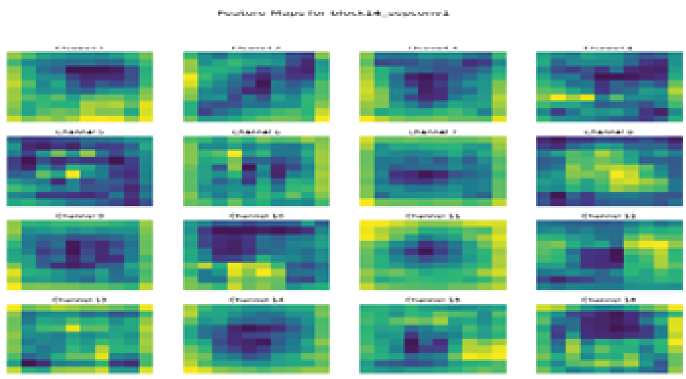

Diagram 5. *Features Extract by Block14_sepconv1*

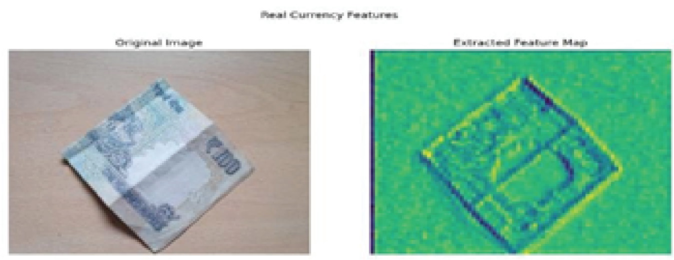

Diagram 6. *Real Currency Extracted Features Map*

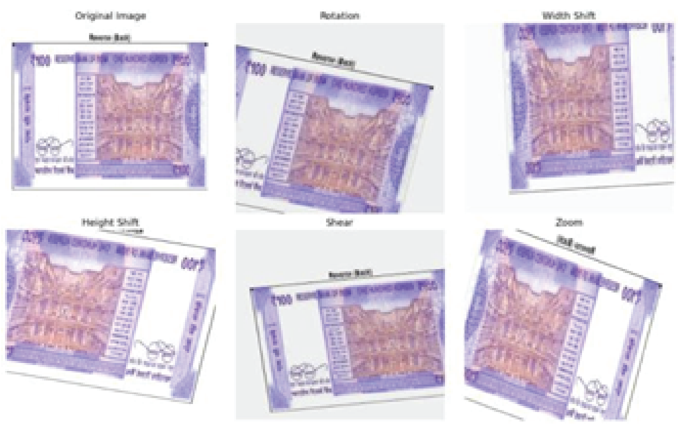

Diagram 4. *Preprocessing of Rs 100 Indian Note*

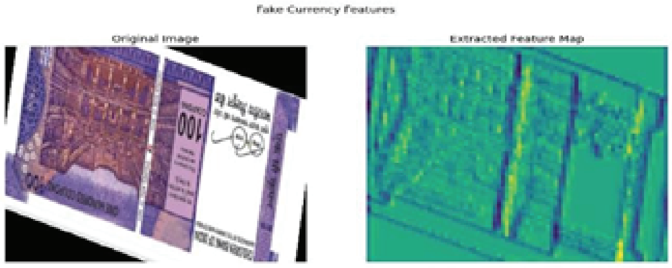

Diagram 7. *Fake Currency Extracted Features Map*

Layer (type)	Output Shape	Param #
xception (Functional)	(None, 10, 10, 2048)	20,861,480
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
dense (Dense)	(None, 512)	1,049,088
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131,328
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 1)	257

Total params: 22,042,153 (84.08 MB)
Trainable params: 1,180,673 (4.50 MB)
Non-trainable params: 20,861,480 (79.58 MB)

Diagram 8. *Model Summary*

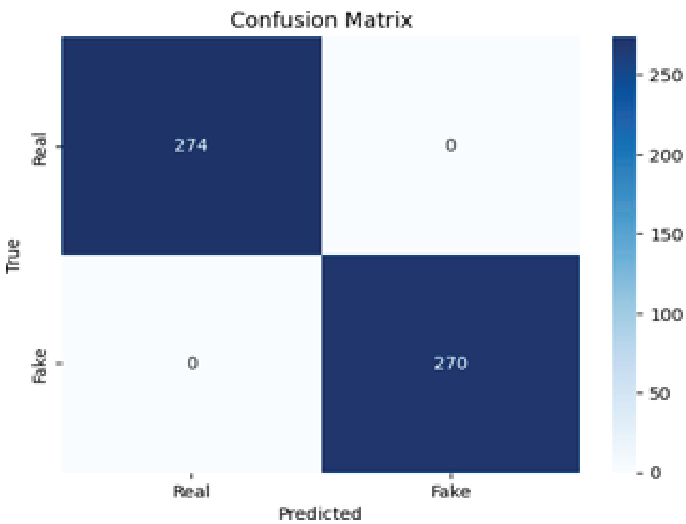

Diagram 9. *Confusion Matrix*

is then ready to be integrated made accessible in web or mobile application, enabling practical world predictions on images of Indian currency.

- **Real-time Prediction:** The saved model is loaded, and the application is set up to take images of currency notes as input. The model predicts whether the currency note is real or fake and provides feedback to the user in real- time.
- **Integration with User Interface:** The model is integrated with a user- friendly interface that allows users to upload currency images. After uploading an image, the system will process it through the model, and the result (real or fake) will be displayed.
- **Final Testing:** The final system is tested with real-world images to evaluate its robustness and accuracy. If necessary, additional retraining is performed to handle edge cases or improve performance.

Implementing hardware module

To implement fake Indian currency detection with the ESP32 Camera module as shown in Diagram 10, the process starts by capturing images of currency notes using the ESP32- CAM. This camera module, featuring a budget- friendly image sensor, transmits the captured images over Wi-Fi to a central server. The server operates a pre-trained machine learning model, like Xception or a custom CNN, which is designed to classify the images as either real or counterfeit. Prior to inputting images into the model, data refinement stages including resizing, normalization, and image augmentation are performed to maintain consistency and enhance robustness. The model undergoes supervised training on labelled samples that includes both real and fake currency images, utilizing frameworks such as Keras or TensorFlow. Once classification is complete, the results are sent back to the ESP32-CAM, offering real-time feedback on the authenticity of the currency.

This configuration presents a practical and cost-effective solution for real-time currency verification, making it suitable for integration into ATMs, kiosks, or point-of-sale systems.

Result analysis and discussion

Performance in detecting fake Indian currency was evaluated using the Xception model on a desktop with a Ryzen 7000 CPU, 8 GB RAM, 512 GB SSD, Windows 11, and an RTX 3060 GPU. Four CNN architectures, AlexNet, Xception, DarkNet53, and ResNet50, were tested on a custom dataset to compare results.. Before feature extraction, the training and testing images went through data augmentation methods like rotation, flipping, and scaling. The average accuracy of the four CNN models was compared. The predicted classes and confusion matrices were obtained using ResNet50, DarkNet53, AlexNet, and Xception. Table II shows the True Positive, True Negative, False Positive, False Negative, and Accuracy values for these

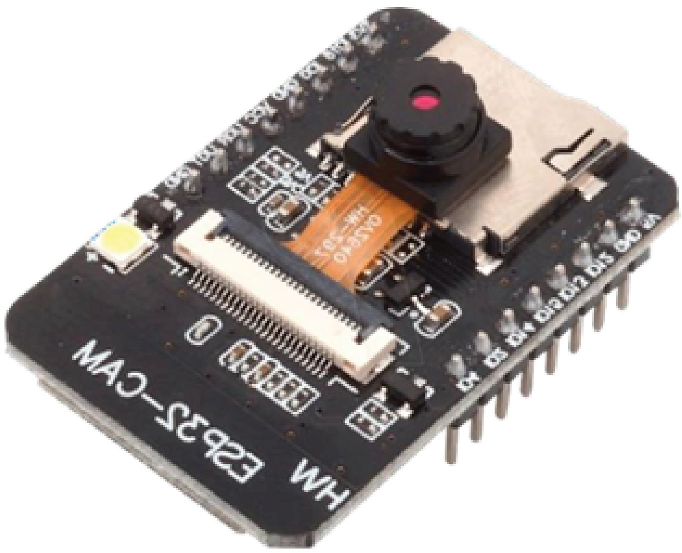

Diagram 10. *ESP 32 Camera*

Table 1. *Formula Table of Precision Recall Accuracy and F1 Scor*

Label	Formula	
Precision	TP / FP + TP	Equation 1
Recall	TP / FN + TP	Equation 2
Accuracy	TP +TN/ TP+TN+FP+FN	Equation 3
F1 Score	2 x Precision x Recall / Precision + Recall	Equation 4

Table 2. T P,F P, F N,T N AND ACCURACY COMPARISON OF FOUR PREDEFINED NETWORKS

Measure	Precision	Recall	F1 Measure	Specific-ity	Youden Index
Dark-net53	77.57	87.62	0.57	74.25	29.6
Alexnet	80.76	43.29	0.55	88.11	31.74
Resnet50	76.77	87.62	0.59	74.25	28.97
Xception	99.99	99.99	0.99	89.1	88.67

Table 3. Precion, Recall, F-Measure, Specificity And Youden Index Of Four Predefined Networks

Measure	TP	FP	FN	TN	Accu-racy
Dark-net53	185	13	51	165	72.04
Alexnet	180	12	55	195	65.15
Resnet50	210	26	59	225	80.94
Xception	274	0	0	270	99.99

four predefined networks. Table III summarizes the Precision, Recall, F- Measure, Specificity, and Youden Index for the same networks. Among them, Xception achieved the highest accuracy of 99.99% and outperformed AlexNet, DarkNet53, and ResNet50. AlexNet had a Precision of 80.76%, while ResNet50 and DarkNet53 achieved a Recall of 87.62%. The F-Measure for Xception was 0.99, and its Specificity was 89.10%. The following performance metrics were calculated for each model: True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN), Accuracy in equation 3,. Precision in equation 1, Recall Rate in equation 2, F1-Measure in equation 4 formula shown in Table 1 and for Xception model the graph of performance Shown in Diagram 11.

Conclusion

Detection of fake Indian currency notes has challenged many in their lives. It has affected public trust as well as the economy and overall stability within the financial sector. Manual fake note detection methods when used bring a lot of errors and inefficiencies to the whole exercise. New-age technologies like image processing, machine learning, and deep learning have thrust counterfeit detection methods into automation and change the way identification becomes a critical process for the identification of counterfeits. Such systems tend to analyze some of these complicated high-security features of notes, such as watermarks, micro-lettering, security threads, and optically variable ink, with accuracy and reliability.

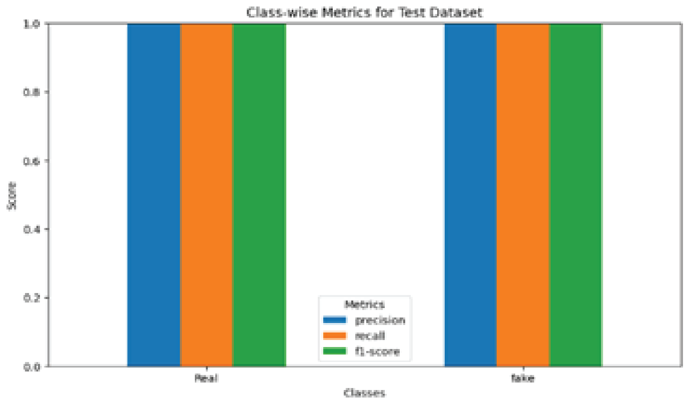

Diagram 11. *Performance Chart of Xception Model*

Recent investigation into Convolutional Neural Networks (CNNs), like ResNet50, DarkNet53, AlexNet, and Xception, has lent a credible ear as regards achieving a cost-effective amount of accuracy as well as precision levels. Real-time detection systems, mostly mobile-type compatible applications, have brought places to people, businesses, and financial institutions. Based on this, some challenges such as lighting conditions variability, data scarcity, and high utilization make it an area of further research and improvement.

The future of heavy, lightweight and scalable models while introducing blockchain or other secure technologies boosts their potential capability for detecting counterfeits. With that continuous innovation and improvement of these systems, it would reduce the possibility of circulation of fake currencies in a secure and trustworthy financial ecosystem.

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