

SUN'IY INTELLEKT YORDAMIDA QALBAKI BANKNOTALARNI REAL VAQT REJIMIDA ANIQLASH: CHUQUR O'RGANISH MODELLARINING SOLISHTIRMA TAHLILI

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Annotatsiya. Qalbaki pulni aniqlash moliyaviy barqarorlik uchun muhimdir. Ushbu ish Hind rupisi banknotalarida chuqur o'rganish, xususan Konvolyutsion Neyron Tarmoqlari va transfer o'rganish (AlexNet, VGG16) asosidagi ikki tadqiqotni ko'rib chiqadi. Ikkala yondashuv real vaqt rejimida yuqori aniqlikni ta'minlaydi. Solishtirma tahlil o'xshashliklar va farqlarni ko'rsatadi, avtomatlashtirilgan qalbaki pul aniqlash tizimlarini ishlab chiqishda foydali xulosalar beradi. Chuqur o'rganish modellari boshqa valyutalarga moslashtirilishi mumkin, aniqlik va samaradorlikni oshiradi.

Kalit so'zlar: Qalbaki pulni aniqlash, Chuqur o'rganish, Konvolyutsion Neyron Tarmog'i (CNN), Qalbaki pul, Transfer o'rganish, Tasvirni qayta ishlash

Аннотация. Обнаружение поддельных банкнот имеет важное значение для финансовой стабильности. В работе рассматриваются два исследования индийских рупий с использованием глубокого обучения, а именно сверточных нейронных сетей и переноса обучения (AlexNet и VGG16). Оба метода демонстрируют высокую точность в реальном времени. Сравнительный анализ выявляет сходства и различия, предоставляя полезные выводы для разработки автоматизированных систем обнаружения подделок. Модели глубокого обучения могут быть адаптированы к другим валютам, обеспечивая точное и эффективное выявление при снижении времени обработки.

Ключевые слова. Обнаружение поддельных банкнот, Глубокое обучение, Сверточная нейронная сеть (CNN), Поддельные деньги, Перенос обучения, Обработка изображений.

Abstract. Detection of counterfeit currency is crucial for financial stability. This work reviews two studies on Indian Rupee banknotes using deep learning, specifically Convolutional Neural Networks and transfer learning with AlexNet and VGG16. Both approaches achieve high accuracy in real-time detection. Comparative analysis highlights similarities and differences, providing insights for developing automated counterfeit detection systems. Deep learning models can be adapted to other currencies, offering precise and efficient detection with reduced processing time.

Keywords. Counterfeit detection, Deep Learning, Convolutional Neural Network (CNN), Fake currency, Transfer Learning, Image Processing

Introduction. Counterfeit currency poses a serious threat to economic stability. It causes financial losses, a loss of public confidence, and complications for banking systems. Conventional techniques used in currency-note recognition rely on either visual inspection, rule-based systems,

or simple image-processing methods. Most of the foregoing techniques are bound to fail when applied to sophisticated forgeries of banknotes.

Deep learning, specifically Convolutional Neural Networks, guarantees a solution to automatically obtain these complex features from banknote images to classify genuine versus counterfeit notes. Transfer learning techniques, such as AlexNet or VGG16, [3] which have been trained on very large datasets, can be adapted to small, specific datasets, therefore hugely reducing training time and computational resources.

The review covers two studies on Indian Rupees, analyzing their methodologies, performance, and applicability to other currencies such as Uzbek Sum:

- Study A (Pruthvi M R et al.): VGG16 CNN [1] trained on a large dataset of Indian banknote images.
- Study B: M. Laavanya & V. Vijayaraghavan - Transfer-learned AlexNet CNN, [3] trained on a smaller dataset of Indian banknote images with real-time detection capabilities.

This is done with the objective of understanding their effectiveness, comparing their results, and discussing the possible adaptation to the Uzbek Sum.

Literature review. 2.1 Study A – VGG16-based Detection [1]

Pruthvi M R et al. employed a deep CNN VGG16 for counterfeit Indian Rupee note detection. Some of the salient features are:

- Dataset: A large set of RGB images is available, including augmented images for robustness.
- Methodology: The images were resized and normalized, fed into VGG16 to extract the features, and classify them as either genuine or counterfeit.
- Performance: Achieved an F1-score of 95.83%, [1] which shows high precision and recall.
- Advantages: Deep feature extraction allows the detection of subtle forgeries, making the model highly reliable.
- Limitations: It requires a large dataset with significant computational resources and processing time.

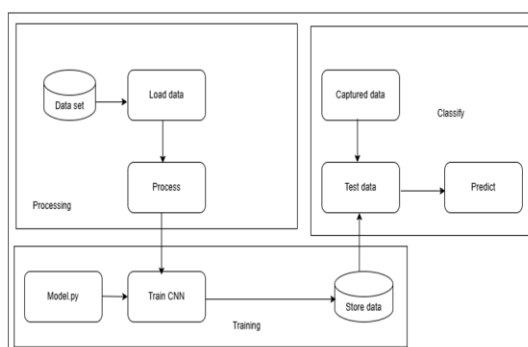


Figure 1. Architectural Diagram

Figure 1 shows the architectural diagram for counterfeit currency detection. At the center is a dataset of images of real and fake banknotes. The images are preprocessed by resizing, normalization, noise reduction, and feature extraction in order to be ready for training. A Convolutional Neural Network (CNN) is trained on this preprocessed data by iteratively adjusting its parameters with an aim of improving performance and reducing overfitting. After successful training, the model is saved for possible deployment. Another different test dataset is used for the evaluation of the generalization ability of the model. Online detection is carried out by feeding

captured images of currency through the CNN, which classifies them as "Real" or "Fake." This architecture makes for efficient and accurate automated authentication of currency.

VGG16 extracts hierarchical features using a combination of convolutional and pooling layers, hence becoming capable of differentiating minor differences among genuine and fake notes, which may be invisible to human vision or conventional image processing.

2.2 Study B – Transfer-learned AlexNet [3]

M. Laavanya & V. Vijayaraghavan performed transfer learning with AlexNet for real-time detection:

- Dataset: 100 images [3] per denomination, augmented to increase training data. It should be noted that the relatively small dataset contributes to lower classification accuracy, particularly for subtle counterfeit features.
- Methodology: Fine-tuning of AlexNet’s last layers to adapt the pretrained weights to the Indian Rupee dataset.
- Performance: Real note accuracy of 81.5% and counterfeit note accuracy of 75%; processing time of ~3 seconds per image. The lower accuracy compared to VGG16 can be attributed to the limited dataset size, even with augmentation.
- Advantages: Faster processing, smaller dataset requirements, feasible for real-time applications.
- Limitations: Slightly lower accuracy compared to VGG16; may miss subtle features that were not learned in the pre-trained model. This highlights the importance of dataset size and diversity in training deep learning models.

Table 1. Experimental Results of the transfer learning Alex Network. [2]

Currency	Real Note	Fake Note	
50	81%	79%	
200	82%	78%	
500	82%	79%	
2000	87%	82%	

AlexNet architecture is comprised of convolutional layers, max pooling, ReLU activations, and fully connected layers. Transfer learning utilizes the knowledge from models already trained on large datasets to boost their performance with fewer data.

Recent Advances in Deep Learning Architectures:

While this review focuses on VGG16 and AlexNet, recent deep learning architectures such as ResNet, EfficientNet, [5] and Vision Transformers (ViT) [2] have demonstrated superior performance in image classification tasks due to better feature extraction, reduced vanishing gradient issues, and efficient parameter usage. Incorporating these architectures in future counterfeit detection studies may further enhance accuracy and computational efficiency.

2.3 Comparative Analysis

Table 1. Comparative Analysis of Deep Learning Approaches for Indian Rupee Counterfeit Detection [5]

Feature / Metric	Study A (VGG16)	Study B (AlexNet)
Dataset	Large RGB images + augmentation	100 images per denomination + augmentation
Denominations	50, 200, 500, 2000 INR	50, 200, 500, 2000 INR

Methodology	VGG16 deep CNN	Transfer-learned AlexNet CNN
Real Note Accuracy	~95% (F1-score)	81.5%
Fake Note Accuracy	~95% (F1-score)	75%
Processing Time	Moderate	Fast (~3 sec per note)
Advantages	High precision, robust feature extraction	Faster, requires smaller dataset
Limitations	Computationally intensive, large dataset required	Slightly lower accuracy, may miss subtle features

The two deep learning approaches, namely, transfer-learned AlexNet by Pruthvi M. R. et al., and VGG16-based approach by M. Laavanya & V. Vijayaraghavan, employed for detecting counterfeit Indian Rupee banknotes are compared in Table 1 with respect to dataset used, size, network architecture, feature extraction methods, training approach adopted, accuracy of detection of real and fake notes, and time consumed in processing together with strengths and limitations in applications:

From the comparison, the following can be concluded:

- Accuracy: VGG16 achieves significantly higher accuracy of 95.83% [8] for both real and fake notes, while AlexNet has only 81.5% of real notes and 75% for fake notes. That means deeper networks with more convolutional layers can capture the intricate features of banknotes better.
- Dataset and Training: AlexNet utilizes a larger raw dataset with transfer learning, whereas VGG16 relies on a much smaller one with heavy augmentation. This demonstrates that deep networks like VGG16 can be highly competitive despite their limitation in original data if proper augmentation is applied.
- Processing Time: AlexNet is lighter and faster to train, hence, suitable for systems with low computational resources. VGG16, although more accurate, involves many more computations, hence a trade-off between speed and precision.
- Feature Extraction: AlexNet focuses on the main security features such as security threads, while VGG16 takes the full image for analysis, extracting deeper convolutional features, hence allowing better generalization for real and counterfeit classification.

Both approaches show the efficacy of deep learning methods for counterfeit detection. AlexNet is faster and resource-efficient but with moderate accuracy, while VGG16 is more computationally expensive but yields higher accuracies. From these reflections, one may realize that a similar deep learning framework like VGG16 could be adopted to detect the fake Uzbek Sum, under the condition of good enough dataset preparation and augmentation to balance the trade-off of accuracy in detection and computational efficiency.

3. Methodology

Both reviewed studies use Convolutional Neural Networks [6] for counterfeit currency detection, though the architecture differs, with similar overall methodology.

Dataset Preparation: Images of genuine and counterfeit banknotes are collected, which undergo some data augmentation-rotation, flipping, and scaling-to increase the dataset size and variation. Similarly, for Uzbek Sum, such a dataset would be needed.



Figure 2. Dataset Screenshot of fake and real currency

Preprocessing: Resizing, normalizing, and converting to RGB channels are done to standardize inputs and bring out key features like colored inks, watermarks, and security threads [4].

Model Training: VGG16 conducts training from scratch to perform hierarchical feature extraction, while AlexNet uses transfer learning by fine-tuning the pre-trained layers on currency detection. Transfer learning is especially useful if the datasets are small.

Table 2. Training Hyperparameters Used in the Experiments [2]

Parameter	VGG16 Model	AlexNet Model
Input image size	$224 \times 224 \times 3$	$224 \times 224 \times 3$
Training approach	Training from scratch / Fine-tuning	Transfer learning
Optimizer	Adam	Adam
Learning rate	0.0001	0.0001
Batch size	32	32
Number of epochs	30	30
Loss function	Categorical Cross-Entropy	Categorical Cross-Entropy
Evaluation metrics	Accuracy, F1-score, processing time	Accuracy, processing time

The network is trained using an augmented dataset, generating 100 images of each banknote by resizing and rotating the images. Then, these images are annotated and stored in labeled folders. Training enables the network to learn features of banknotes of 2000, 500, 200, and 50 denominations [9]. The system used comprises an Intel Core i3 processor, 4 GB RAM, Windows 10, and MATLAB 2018a. To give impetus to feature learning in fully connected layers, hyperparameters are optimized. Images captured through a webcam during real-time testing are matched with the learned features, and then the network classifies them into “Real Note” or “Fake Note” (see Figure 3).

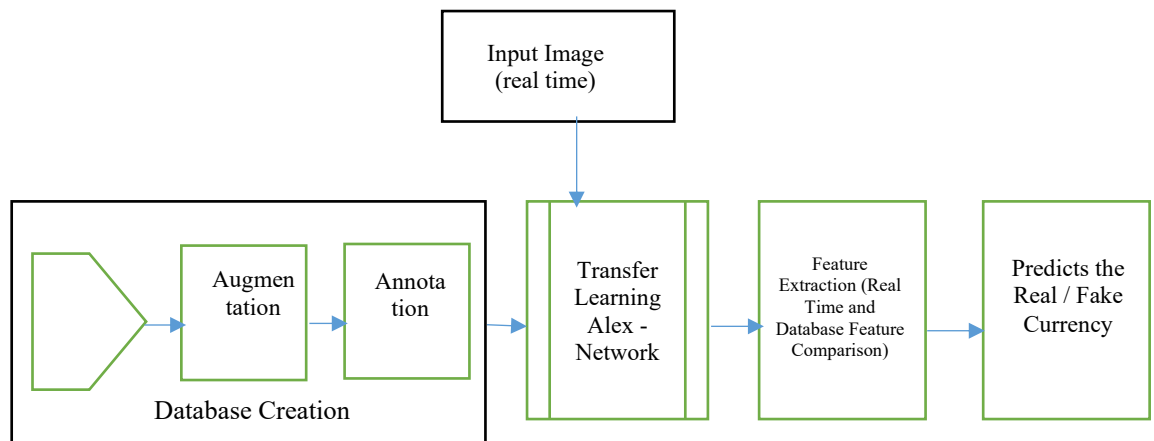


Figure 3. Work flow of proposed scheme (author's own work)

Feature Extraction: CNNs automatically extract such features as security threads, textures, and watermarks, reducing reliance on manual feature design [7].

Classification: The fully connected layers output the probability of genuine vs. counterfeit banknotes, using softmax activation.

Evaluation: Accuracy, F1-score, and processing time are measured. VGG16 achieves higher accuracy, while AlexNet offers faster processing with slightly lower accuracy.

Adaptation to Uzbek Sum: The approach can be reused here with minor modifications: collecting the dataset of banknotes in Uzbek, performing augmentation, and fine-tuning the pre-trained CNN model. Features specific to Uzbek currency should be considered for more accurate detection.

4. Steps in Model Development for Adjustment to Uzbek Sum

1. **Dataset Creation:** Collect images of Uzbek Sum banknotes, both authentic and counterfeit, with high resolution, in varying light and angles. Use methods such as rotation, flip, and scale in order to augment this dataset.

2. **Preprocessing:** Resize all images into a 224x224 matrix, and apply normalization to the RGB channels. Additionally, focus on improving key security elements including watermarks, security threads, and microtext.

3. **Model Fine-Tuning:** The VGG16 or AlexNet model can be used and fine-tuned in terms of the last convolutional layers and fully connected layers using the Uzbek Sum dataset in order to adjust to local currency characteristics.

4. **Evaluation:** Calculate accuracy, F1-score, and processing time. Perform qualitative analysis of wrongly classified instances to spot possible flaws. 5. **Real-Time Execution:** Implement your optimized model into a camera network for executing real-time detections in a banking hall or a retail setup.

5. Discussion

5.1 Advantages of Deep Learning for Currency Detection

Automated and Accurate Detection: Deep learning models minimize human errors since they learn complex patterns automatically to distinguish between genuine and counterfeit banknotes.

Subtle Difference Detection: CNNs can detect minute differences in textures, holograms, watermarks, and threads that may not be noticed through conventional image processing or manual inspection.

Adaptability to New Currencies: Transfer learning enables models trained on one currency (e.g., Indian Rupees) to adapt to another currency (e.g., Uzbek Sum) with minimal retraining.

Reduced human effort and processing time: Automation allows banks and retail stores to quickly verify notes, reducing the workload and time taken by manual inspection.

5.2 Challenges

The datasets have to be in good quality and well-labeled. Poor datasets may result in poor generalization and reduced accuracy.

Differences in Design: Not all currencies have the same security features; therefore, fine-tuning of pretrained models or custom preprocessing is necessary with new notes.

Computational Resources: Training deep CNNs requires significant computational power, especially when large datasets or high-resolution images are used. Efficient training using a GPU or cloud services may be needed. **Real-World Variability:** The notes in circulation may be worn, dirty, or even partially damaged. The model should be insensitive to this kind of variation to ensure dependable detection under practical conditions.

6. Conclusion and Future Work

This review and comparative analysis of two studies on Indian Rupee banknotes illustrates that deep learning, in particular CNNs like VGG16 and AlexNet, is very effective for fake currency detection.

VGG16 Architecture: Provides high precision owing to deep convolutional layers but, however, the model is computationally expensive and requires a large and well-annotated dataset.

Transfer-Learned AlexNet: Fine-tuning a pre-trained AlexNet on a smaller dataset allows faster training and detection in real-time, suitable for practical applications in banks and retail.

Implications for Uzbek Sum

These methods can also be applied to Uzbek Sum. Using a dedicated dataset, comprising real and counterfeit banknotes, CNN models can be fine-tuned to learn local security features such as watermarks, threads, and holograms. This approach minimizes the necessity of very large datasets for achieving high accuracy with the help of transfer learning.

Future Directions:

Data creation: high-resolution images of Uzbek Sum notes in all kinds of conditions, augmented to ensure robustness.

Model Fine-Tuning: Adapt CNNs to capture special features of Uzbek currency. Explore various architectures for a tradeoff between accuracy and speed.

Real-Time Testing: Test models in banks, retail, and currency exchange for a realistic performance evaluation.

Comparative Analysis: Test different CNN architectures in order to optimize accuracy vs. processing time.

Key Takeaway:

The various deep learning models that were tested on Indian Rupees can be fine-tuned for Uzbek Sums to enable accurate and efficient counterfeit detection without much human effort and processing time.

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