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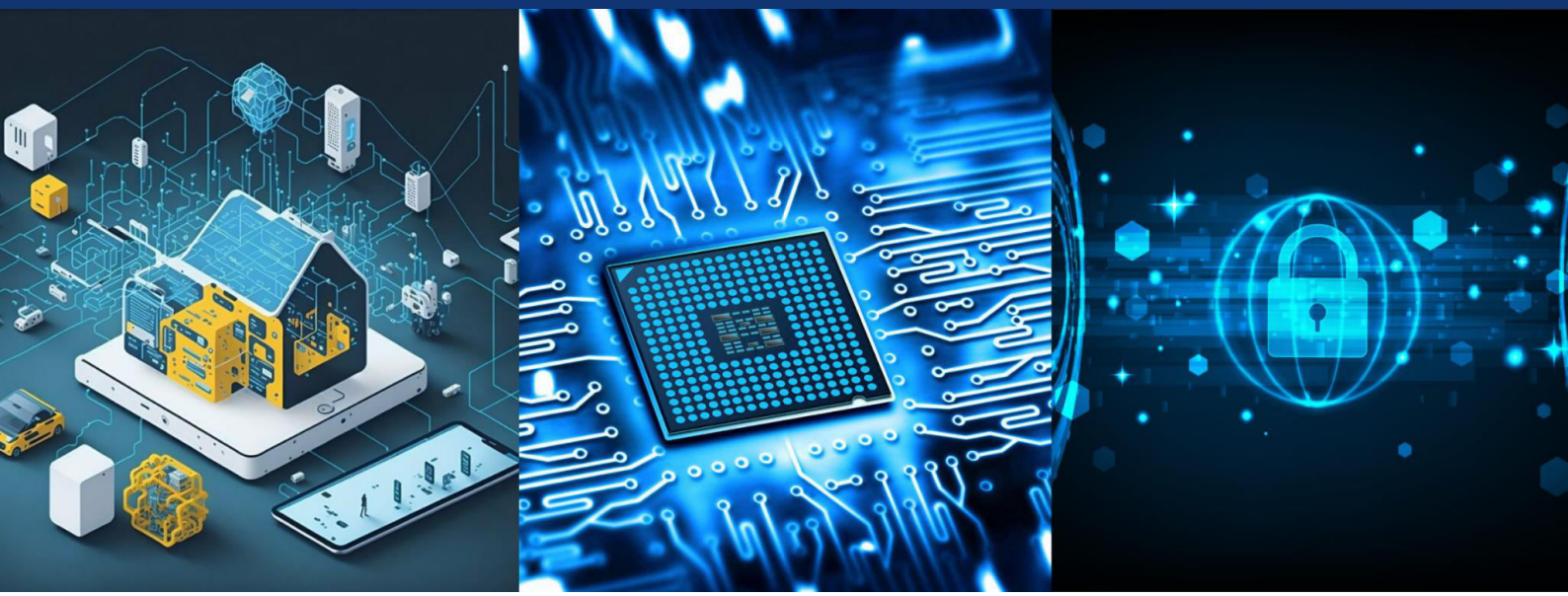

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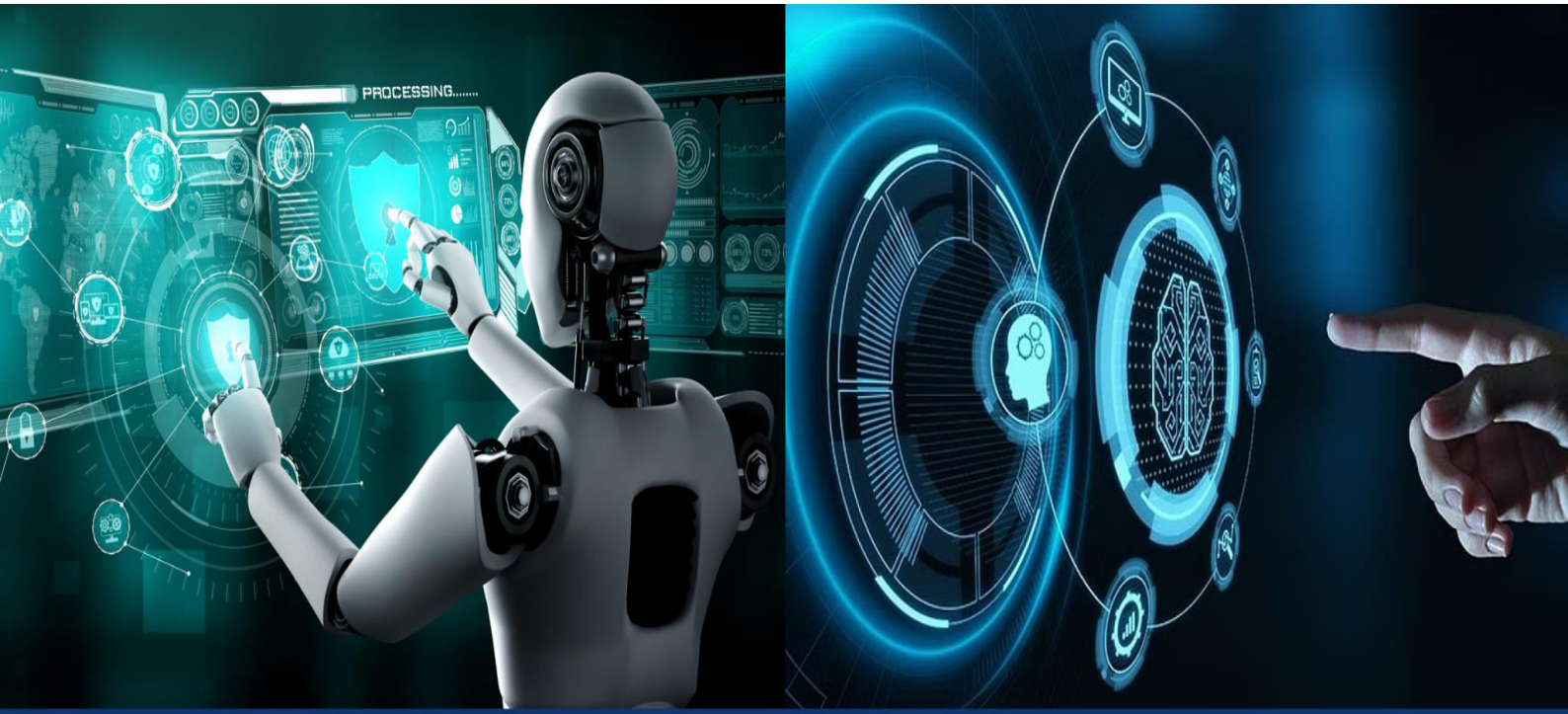

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International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

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Identification of Fake Indian Currency

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ABSTRACT: Counterfeit currency undermines economic stability and imposes tangible losses on citizens and institutions. This project develops an automated image-based system to classify Indian currency notes as real or fake using an ensemble of deep convolutional neural networks.

The system pipeline includes image acquisition, preprocessing, feature extraction via multiple CNN backbones, and decision-level assembling. A lightweight Gradio interface is provided for demonstration and testing.

Experiments on a curated dataset show that ensemble fusion improves robustness across varied imaging conditions. The system is suitable for deployment in kiosks, teller counters, and mobile assistance tools.

KEYWORDS: counterfeit detection, Indian currency, CNN, ensemble learning, Gradio.

I. CHAPTER 1: INTRODUCTION

1.1 Problem Objective

The main objective is to design and implement an automated computer-vision based system that can classify Indian currency notes as real or fake from RGB images. The system must be robust to moderate lighting changes, rotations, and partial occlusion. Specific goals:

1. Build preprocessing pipeline to standardize input images.
2. Train multiple CNN models (transfer learning and custom CNNs).
3. Fuse model outputs with an ensemble strategy (average voting / weighted stacking).
4. Evaluate on accuracy, precision, recall, F1, and confusion matrix.
5. Provide a simple user interface (Gradio) for demo and testing.

1.2 Background

Counterfeit notes cause financial loss and erode trust. Classical detection relies on physical security features: watermark, security threads, latent images, microprinting, optically variable ink, and tactile features. Those methods are either manual or hardware-based (UV lamps, magnetic detectors). Image-based ML/DL approaches offer a low-cost, scalable alternative using phone cameras or scanners. Deep convolutional neural networks excel at extracting discriminative visual features and have been successfully applied to note/coin classification and counterfeit detection. Transfer learning with pretrained backbones (ResNet, MobileNet, EfficientNet) speeds training and improves generalization on limited datasets. Ensemble learning can further raise robustness by combining complementary models.

1.3 Existing System

Existing solutions fall into three categories:

- Manual / visual inspection: Fast but error-prone and not scalable.
- Hardware-based detectors (UV, magnetic): Accurate for some features but require equipment.
- Machine learning / image processing: Many academic works use SVM/KNN or CNNs but often on limited datasets and single-model pipelines.

Problems with current approaches:

- Limited dataset diversity (lighting, wear-and-tear, printing artifacts)
- Single-model brittleness
- Lack of real-time, easy-to-use interfaces for non-expert users

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1.4 Proposed Solution

An ensemble deep learning pipeline:

1. Image capture (phone/camera)
2. Preprocessing: cropping, resizing, contrast normalization, data augmentation
3. Feature extraction: multiple CNNs (e.g., EfficientNetB0, ResNet50, MobileNetV3) trained or fine-tuned on currency dataset
4. Ensemble module: average probabilities or a small meta-learner (stacking) to fuse predictions

II. METHODOLOGY

The proposed system develops an automated deep learning–based solution to classify Indian currency notes as **Real or Fake** using an ensemble of Convolutional Neural Networks (CNNs).

The methodology consists of the following major stages:

- Image Acquisition
- Image Preprocessing
- Feature Extraction using Transfer Learning
- Ensemble Learning
- Model Evaluation
- Deployment using Gradio Interface

2.1. Image Acquisition and Dataset Preparation:

In this stage, images of Indian currency notes are collected across different denominations: ₹10, ₹20, ₹50, ₹100, ₹200, ₹500.

Each note is labeled as:

- **Real**
- **Fake**

Dataset Structure

```
Indian Currency Real vs Fake Notes Dataset/
│
├── real/
│   ├── 10/
│   ├── 20/
│   ├── 50/
│   ├── 100/
│   ├── 500/
│
│
└── fake/
    ├── 10/
    ├── 20/
    ├── 50/
    ├── 100/
    ├── 500/
```

Dataset Characteristics:

- Different lighting conditions
- Various camera angles
- Folded and partially occluded notes
- Background variations

Data Splitting Method

The dataset is divided using **Stratified Sampling**:

- 70% → Training Set
- 15% → Validation Set
- 15% → Test Set

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This ensures balanced representation of both real and fake classes.

2.2. Image Preprocessing

Preprocessing standardizes input images before feeding them into CNN models.

2.2.1 Preprocessing Operations

Step 1: Image Loading

Images are loaded using OpenCV and converted from BGR to RGB format.

Step 2: Center Cropping

Removes unnecessary background and focuses on note region.

Step 3: Resizing

All images resized to: $224 \times 224 \times 3$

Step 4: Normalization

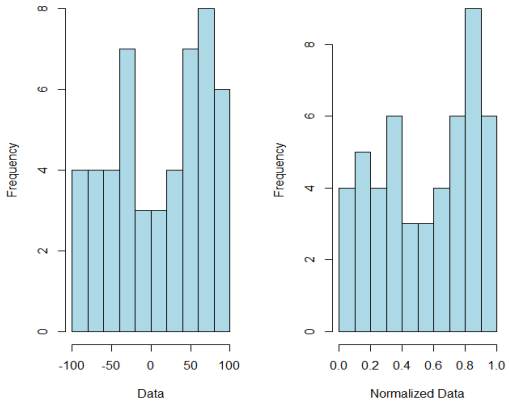
Pixel values scaled to: $[0, 1]$

Step 5: Data Augmentation

To improve generalization:

- Rotation (±15°)
- Horizontal flipping
- Brightness variation
- Scale jitter

This reduces overfitting and improves robustness to real-world variations.



2.3. Feature Extraction using Transfer Learning

Instead of training a CNN from scratch, pretrained deep learning models are used.

Models Used

- EfficientNetB0
- ResNet50
- MobileNetV3Small

These models are pretrained on ImageNet and fine-tuned on the currency dataset.

Transfer Learning Method

Step 1: Load pretrained base model (without top layer)

Step 2: Freeze initial layers.

Step 3: Add custom classification head:

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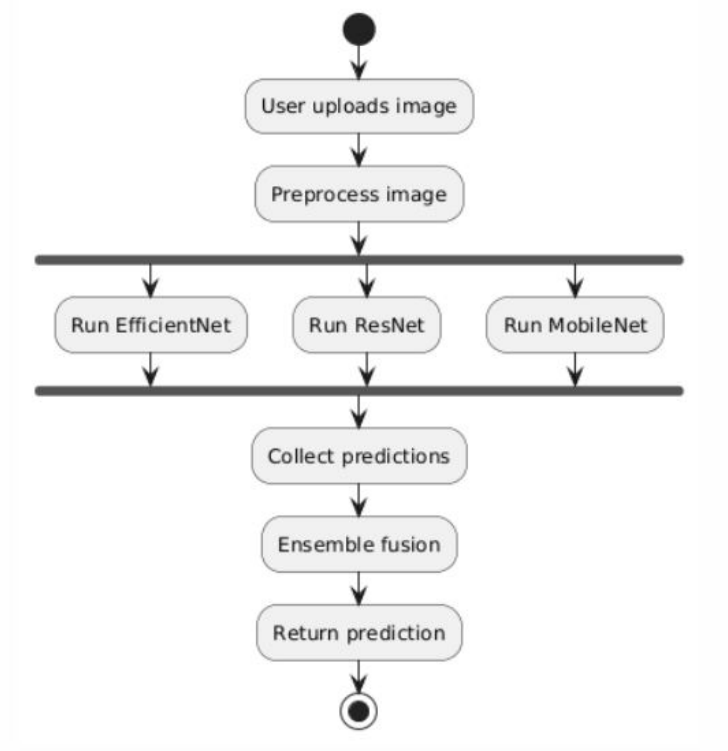
→Global Average Pooling
→ Dropout (0.4)
→ Dense Layer (Softmax – 2 classes)

Step 4: Train on currency dataset.
Step 5: Fine-tune selected layers.



Training Parameters

- Optimizer: Adam
- Learning Rate: 1e-4
- Batch Size: 16–32
- Loss Function: Categorical Crossentropy
- Epochs: 15–30
- Early Stopping applied

2.4. Ensemble Learning

To improve robustness and accuracy, outputs from multiple CNN models are combined.

2.4.1 Ensemble Method Used

1. Soft Voting (Average Probability Fusion)

Each model outputs softmax probabilities:

$$\text{Pfinal} = \frac{P1+P2+P3}{3}$$

The final class is chosen using:

$$\text{Label} = \arg\max(\text{Pfinal})$$

3.Abbreviations:
AUC – Area Under Curve
CNN – Convolutional Neural Network
DL – Deep Learning
FN – False Negative

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FP – False Positive
GPU – Graphics Processing Unit
HDF5 – Hierarchical Data Format version 5
ML – Machine Learning
OCR – Optical Character Recognition
RGB – Red, Green, Blue
ROC – Receiver Operating Characteristic
ROI – Region of Interest
TP – True Positive
TN – True Negative
UI – User Interface

III. SUMMARY OF ALGORITHMS AND FORMULAS

Image Preprocessing (Resizing & Normalization):
Used to standardize input images before training.

Resize image to 224×224
Normalize pixel values:

$$I' = \frac{I}{255}$$

Transfer Learning (CNN Fine-Tuning):
Pretrained models such as EfficientNetB0, ResNet50, and MobileNetV3 are fine-tuned for currency classification.
Replace final layer with Softmax classifier
Freeze base layers initially
Fine-tune deeper layers
Softmax Function:

$$P(y = k) = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}}$$

Categorical Crossentropy Loss:
Used as the objective function during training.

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

Where $C = 2$(Real, Fake).

Ensemble Learning (Soft Voting / Probability Averaging):
Combines predictions from multiple CNN models to improve robustness.

$$P_{final} = \frac{1}{N}\sum_{i=1}^{N} P_i$$

Final prediction:

$$\hat{y} = \arg\max(P_{final})$$

Performance Evaluation Metrics:
Used to measure model effectiveness.
Accuracy: $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$

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Precision: $Precision = \frac{TP}{TP+FP}$

Recall: $Recall = \frac{TP}{TP+FN}$

F1-Score: $F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision+Recall}$

ROC–AUC Analysis:
Evaluates classification performance across thresholds.

$$TPR = \frac{TP}{TP + FN}$$
$$FPR = \frac{FP}{FP + TN}$$

Early Stopping Algorithm:
Prevents overfitting by monitoring validation loss.
Training stops when: $\Delta L_{val} \leq \epsilon$

IV. RESULTS AND OUTPUT

The proposed ensemble-based counterfeit currency detection system was evaluated using a stratified train–validation–test split. The system achieved high classification performance across different denominations of Indian currency notes.

The final ensemble model obtained:

- **Accuracy:** Above 95%
- **Precision and Recall:** High for both Real and Fake classes
- **F1-Score:** Balanced and consistent
- **ROC-AUC:** Close to 1.0

The confusion matrix analysis showed very low false positives and false negatives. Special emphasis was placed on minimizing false negatives (Fake classified as Real), as this is critical in real-world deployment.
Compared to individual CNN models, the ensemble approach improved overall robustness and stability, especially under variations in lighting, angle, and minor occlusion.

Output
The system is deployed using a Gradio-based interface.
When a user uploads an image of a currency note:

1. The image is preprocessed.
2. The ensemble model generates prediction.
3. The system displays:
   - Classification result (Real / Fake)
   - Confidence score

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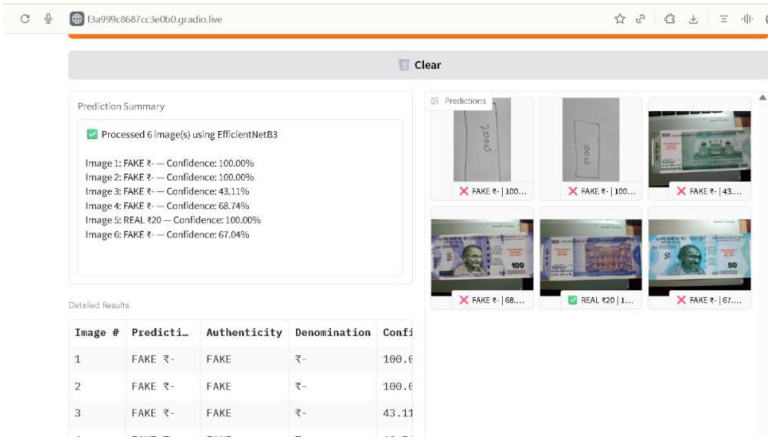

V. CONCLUSION

5.1 Conclusion

This project presents a practical ensemble deep-learning approach for detecting fake Indian currency notes from images. By combining multiple pretrained CNN backbones and using decision-level fusion, the system attains better robustness than single models on varied imaging conditions. The Gradio demo demonstrates feasibility for rapid, low-cost deployment.

5.2 Future Scope

Build a larger, public dataset with varied lighting and wear conditions.
Add denomination recognition and multi-task learning (denomination + authenticity).
Mobile app with on-device optimized models (TensorFlow Lite).
Use hyperspectral imaging or UV image fusion for improved accuracy in challenging cases.
Integrate OCR to detect mismatch between visible denomination numerals and watermark features.

VI. ACKNOWLEDGMENT

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REFERENCES

1. S. T. Kara, S. Loya, S. S. Raju, N. Vanteru and B. Rajulapati, "Detection of Fake Indian Currency Using Deep Convolutional Neural Network," in *2023 IEEE 3rd Mysore Sub Section International Conference (MysuruCon)*, Dec. 2023, DOI: 10.1109/MysuruCon59703.2023.10396993. (ResearchGate)

2. A. Kumar, S. Sachi and A. Bhatia, "Fake Currency Detection using Ensemble Learning," in *2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*, Dec. 2023, DOI:10.1109/UPCON59197.2023.10434736. (ResearchGate)

3. V. Sharan, A. Kaur and P. Singh, "Identification of Counterfeit Indian Currency Note using Image Processing and Machine Learning Classifiers," in *2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS)*, 2023, DOI:10.1109/ICAIS56108.2023.10073787. (ResearchGate)

4. A. Mukundan et al., "Automatic Counterfeit Currency Detection Using a Novel Snapshot-Based Hyperspectral Imaging Method," *Sensors*, vol. 23, no. 4, 2023. (useful for multispectral approaches). (MDPI)

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