IMAGE-BASED INDIAN BANKNOTE AUTHENTICATION USING AI AND CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

The circulation of counterfeit Indian banknotes remains a significant challenge for financial security and economic stability. Traditional counterfeit detection methods rely on manual verification, ultraviolet scanning, or embedded watermark features. However, these methods are time-consuming, prone to human error, and inaccessible in rural or low-resource environments. With rapid advancements in artificial intelligence (AI) and computer vision, automated solutions for currency authentication have gained momentum. This study proposes an image-based banknote authentication system leveraging deep learning, specifically Convolutional Neural Networks (CNNs). The system is designed to detect fake Indian currency using high-resolution images captured via mobile devices or scanners. Images of Indian banknotes are pre-processed through resizing, grayscale conversion, and noise reduction techniques. Data augmentation methods such as rotation, flipping, and contrast adjustment are employed to improve model generalization. The dataset comprises both genuine and counterfeit Indian currency notes of various denominations. A CNN model is trained on these images to learn distinct spatial and texture features. The architecture includes multiple convolutional layers for feature extraction, pooling layers for dimensionality reduction, Rectified Linear Unit (ReLU) activations for non-linearity, dropout layers to prevent overfitting, and fully connected layers that map extracted features to classification outputs. A softmax function generates probability distributions across the two classes: genuine and counterfeit. The model is trained using cross-entropy loss and optimized with the Adam optimizer, while hyperparameter tuning determines the optimal learning rate, batch size, and epochs. Performance metrics such as accuracy, precision, recall, and F1-score are employed. The system demonstrates high accuracy in distinguishing real from fake currency notes and outperforms traditional classifiers such as SVM and Random Forest. It is capable of identifying intricate counterfeit patterns invisible to the naked eye, with classification accuracy exceeding 95% in trials. Real-time testing confirms that predictions can be made within seconds on consumer-grade hardware. Integration with smartphone applications makes the solution portable and accessible, enabling deployment at retail shops, banks, and ATMs. The framework is scalable for multi-denomination recognition and can be integrated with cloud platforms for central monitoring. Security measures are embedded to prevent

adversarial attacks, and the system contributes to reducing financial fraud while aligning with India's vision of AI-driven fintech innovation. Limitations include dependency on high-quality images and dataset diversity, but future work will expand datasets, apply transfer learning with architectures such as VGG16, ResNet50, or EfficientNet, and integrate explainable AI (XAI) to highlight counterfeit features. Hybrid approaches combining CNNs with IoT-based scanners and blockchain-backed logging will further enhance resilience. The system can extend beyond Indian currency, supporting global anti-counterfeiting initiatives.The proliferation of counterfeit currency poses a significant challenge to global economies, undermining financial stability and consumer confidence. Traditional methods of detecting counterfeit currency often fall short due to their reliance on manual inspection and limited technological capabilities. This study explores the application of Convolutional Neural Networks (CNNs) in detecting counterfeit currency, leveraging advanced deep learning techniques to automate and enhance the accuracy of the detection process. By training CNN models on large datasets of both genuine and counterfeit currency images, the proposed method aims to identify subtle differences and security features that distinguish authentic notes from counterfeit ones. The results demonstrate that CNN-based approaches significantly outperform traditional methods, offering a robust and scalable solution for real-time counterfeit currency detection.

Key Words: Fake currency, CNN, Deep learning, Counterfeit.

INTRODUCTION

Counterfeit currency is a persistent problem that affects economies worldwide, leading to substantial financial losses and undermining the trust in monetary systems. Traditional counterfeit detection methods, which often rely on manual inspection or basic image processing techniques, are increasingly inadequate in the face of sophisticated counterfeiting technologies. As counterfeiters become more adept at replicating the security features of genuine currency, there is a pressing need for more advanced and automated detection systems.

Importance of Counterfeit Detection

The detection of counterfeit currency is crucial for maintaining the integrity of financial transactions and protecting consumers from fraud. Inaccurate or delayed detection can lead to significant economic damage, affecting businesses, individuals, and governments. Therefore, enhancing the accuracy and efficiency of counterfeit detection systems is of paramount importance.

Advancements in Deep Learning

Recent advancements in deep learning, particularly in the field of image recognition, have opened new avenues for tackling the problem of counterfeit currency detection. Convolutional Neural Networks (CNNs) have proven to be exceptionally effective in various image classification tasks, making them a promising tool for detecting counterfeit notes. CNNs are capable of learning complex patterns and features from large datasets, which can be applied to distinguish between genuine and counterfeit currency with high precision.

OBJECTIVE

This study aims to develop a CNN-based counterfeit currency detection system that can

automatically and accurately identify counterfeit notes. By leveraging the power of deep learning, the proposed system seeks to overcome the limitations of traditional methods and provide a scalable solution for real-time detection.

LITERATURE SURVEY

In this paper, the authors present a method for detecting and recognizing counterfeit currency using convolutional neural networks (CNNs). The study leverages a deep learning approach, specifically a CNN, to extract features from currency images. The proposed model is trained on a dataset of both genuine and counterfeit currency images, and it achieves high accuracy in detecting counterfeit notes. The authors highlight the robustness of their model in handling various image conditions, such as different lighting and background scenarios, which is critical for real-world applications As per Mark (2021) . propose an efficient model for fake currency detection using CNNs. The model is designed to identify intricate patterns and security features embedded in currency notes that are challenging to replicate accurately in counterfeit versions. The authors use a dataset of high-resolution currency images to train their CNN model, achieving remarkable precision and recall rates. They emphasize the importance of using high-quality images to improve the model's performance and reduce false positives and negatives . This paper explores the application of CNNs combined with transfer learning techniques for counterfeit currency detection. Dr.Naveen Prasadula (2023) utilize pre-trained models like VGG16 and ResNet50, which are fine-tuned with a specific dataset of currency images. The study demonstrates that transfer learning significantly enhances the model's performance by leveraging pre-existing knowledge from large-scale image datasets. The results show a considerable improvement in detection accuracy compared to traditional machine learning approaches. steve (2021) introduce a hybrid model that combines CNNs with Support Vector Machines (SVM) for detecting counterfeit currency. The CNN component is responsible for feature extraction, while the SVM classifier is used for final classification. This hybrid approach aims to leverage the strengths of both techniques, achieving higher accuracy and faster processing times. The paper reports that the hybrid model outperforms standalone CNN and SVM models, particularly in handling complex and noisy currency images . Farid (2022) present an automated system for fake currency detection using CNNs. The proposed system incorporates a multi-stage CNN architecture to progressively refine feature extraction and improve detection accuracy. The authors evaluate their model on a diverse dataset of currency images, including notes from different countries and denominations. The experimental results demonstrate the system's effectiveness in accurately identifying counterfeit notes, highlighting its potential for real-

world deployment .

METHODOLOGY

Data Collection and Image Pre-processing

1. **Data Collection**:
   - Collect a comprehensive dataset of images of Indian currency notes, including both genuine and counterfeit notes.
   - Ensure a diverse representation of different denominations and variations in note conditions.
2. **Image Preprocessing**:
   - **Resizing**: Standardize the size of all images to ensure uniform input dimensions for the CNN.
   - **Grayscale Conversion**: Convert images to grayscale to reduce computational complexity while preserving essential features.
   - **Noise Reduction**: Apply filters to remove noise and enhance image quality.
   - **Normalization**: Normalize pixel values to a range of [0, 1] to improve model training efficiency.

```
project/
├─ requirements.txt
├─ train.py
├─ infer.py
├─ api_service.py
├─ gradcam.py
└─ data/
   ├─ train/
   │  ├─ genuine/  # images of real INR notes (all denominations)
   │  └─ counterfeit/  # images of fake INR notes
   ├─ val/
   │  ├─ genuine/
   │  └─ counterfeit/
   └─ test/
      ├─ genuine/
         └─ counterfeit/
```

FEATURE EXTRACTION AND MODEL TRAINING

1. **Feature Extraction**:
   - Use convolutional layers to automatically extract relevant features from the input images.
   - Apply pooling layers to reduce dimensionality and capture spatial hierarchies.
2. **Model Architecture**:
   - Design a CNN model with multiple convolutional and pooling layers, followed by fully connected layers.
   - Implement dropout layers to prevent overfitting and improve model generalization.
3. **Training and Validation**:
   - Split the dataset into training, validation, and test sets.
   - Train the CNN model using the training set, optimizing it with an appropriate loss function and optimizer (e.g., cross-entropy loss and Adam optimizer).
   - Validate the model using the validation set to tune hyperparameters and prevent overfitting.
   - import argparse, os, time, json
   - from pathlib import Path
   - import numpy as np
   - import torch
   - import torch.nn as nn
   - from torch.optim import AdamW
   - from torch.optim.lr_scheduler import OneCycleLR
   - from torch.utils.data import DataLoader, WeightedRandomSampler
   - from torchvision import datasets, transforms, models
   - from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score
   - from tqdm import tqdm
   -

```
def build_transforms(image_size=384):
    # Currency-specific: preserve fine textures; use modest color jitter; mild blur/edges can help robustness
    train_tf = transforms.Compose([
        transforms.Resize((image_size, image_size)),
        transforms.RandomApply([transforms.ColorJitter(0.2,0.2,0.2,0.1)], p=0.6),
```

```
        transforms.RandomRotation(5),
        transforms.RandomResizedCrop(image_size, scale=(0.9, 1.0), ratio=(0.95, 1.05)),
        transforms.RandomHorizontalFlip(p=0.1),  # small chance (notes are usually not
mirrored)
        transforms.GaussianBlur(kernel_size=3, sigma=(0.1, 1.0)),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485,0.456,0.406], std=[0.229,0.224,0.225])
    ])
    eval_tf = transforms.Compose([
        transforms.Resize((image_size, image_size)),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485,0.456,0.406], std=[0.229,0.224,0.225])
    ])
    return train_tf, eval_tf
def count_per_class(ds):
    targets = [y for _, y in ds]
    cls_counts = np.bincount(targets)
    return cls_counts
def get_class_weights(counts):
    # inverse frequency
    weights = 1.0 / (counts + 1e-6)
    weights = weights / weights.sum() * len(counts)
    return weights
def build_dataloaders(data_dir, img_size, batch_size, num_workers):
    train_tf, eval_tf = build_transforms(img_size)
    train_ds = datasets.ImageFolder(Path(data_dir)/"train", transform=train_tf)
    val_ds   = datasets.ImageFolder(Path(data_dir)/"val",   transform=eval_tf)
    # Class-imbalance handling
    counts = count_per_class(datasets.ImageFolder(Path(data_dir)/"train",
transform=eval_tf))
    cls_weights = get_class_weights(counts)  # per-class
    sample_weights = [cls_weights[target] for _, target in train_ds]
    sampler = WeightedRandomSampler(sample_weights,
num_samples=len(sample_weights), replacement=True)
```

```
    train_loader = DataLoader(train_ds, batch_size=batch_size, sampler=sampler,
                              num_workers=num_workers, pin_memory=True)
    val_loader   = DataLoader(val_ds, batch_size=batch_size, shuffle=False,
                              num_workers=num_workers, pin_memory=True)
    return train_loader, val_loader, train_ds.classes

def build_model(num_classes=2, backbone="resnet50", pretrained=True):
    if backbone == "resnet50":
        model = models.resnet50(weights=models.ResNet50_Weights.DEFAULT if
pretrained else None)
        in_feat = model.fc.in_features
        model.fc = nn.Sequential(
            nn.Linear(in_feat, 512),
            nn.ReLU(inplace=True),
            nn.Dropout(0.3),
            nn.Linear(512, num_classes)
        )
    elif backbone == "efficientnet_b3":
        model =
models.efficientnet_b3(weights=models.EfficientNet_B3_Weights.DEFAULT if
pretrained else None)
        in_feat = model.classifier[-1].in_features
        model.classifier[-1] = nn.Linear(in_feat, num_classes)
    else:
        raise ValueError("Unsupported backbone")
    return model

def evaluate(model, loader, device):
    model.eval()
    y_true, y_prob, y_pred = [], [], []
    ce = nn.CrossEntropyLoss(reduction="sum")
    loss_tot, n = 0.0, 0
    with torch.no_grad():
        for x, y in loader:
            x, y = x.to(device), y.to(device)
```

```
            logits = model(x)
            loss = ce(logits, y)
            prob = torch.softmax(logits, dim=1)[:,1]
            pred = logits.argmax(1)
            loss_tot += loss.item()
            n += y.size(0)
            y_true.extend(y.tolist())
            y_pred.extend(pred.tolist())
            y_prob.extend(prob.tolist())
    acc = (np.array(y_true) == np.array(y_pred)).mean()
    try:
        auc = roc_auc_score(y_true, y_prob)
    except:
        auc = float("nan")
    return loss_tot/n, acc, auc, y_true, y_pred
def main():
    ap = argparse.ArgumentParser()
    ap.add_argument("--data_dir", type=str, default="data")
    ap.add_argument("--epochs", type=int, default=20)
    ap.add_argument("--batch_size", type=int,
```

MODEL EVALUATION

1. **Accuracy**:
   - Evaluate the model's accuracy on the test set to determine its ability to correctly classify genuine and counterfeit notes.
   - Compare the accuracy with other state-of-the-art methods to establish the model's effectiveness.
2. **Confusion Matrix**:
   - Use a confusion matrix to analyze the model's performance in terms of true positives, true negatives, false positives, and false negatives.
   - Calculate precision, recall, and F1-score to provide a comprehensive evaluation of the model.

```
import torch
import torch.nn.functional as F
```

```
import numpy as np
from PIL import Image

class GradCAM:
    def __init__(self, model, target_layer):
        self.model = model.eval()
        self.target_layer = target_layer
        self.gradients = None
        self.activations = None

        def fwd_hook(module, inp, out):
            self.activations = out.detach()
        def bwd_hook(module, grad_in, grad_out):
            self.gradients = grad_out[0].detach()

        self.fh = target_layer.register_forward_hook(fwd_hook)
        self.bh = target_layer.register_full_backward_hook(bwd_hook)

    def __call__(self, x, class_idx):
        self.model.zero_grad(set_to_none=True)
        logits = self.model(x)
        score = logits[:, class_idx].sum()
        score.backward(retain_graph=True)

        grads = self.gradients  # [B, C, H, W]
        acts  = self.activations
        weights = grads.mean(dim=(2,3), keepdim=True)
        cam = (weights * acts).sum(dim=1, keepdim=True)
        cam = F.relu(cam)
        cam = F.interpolate(cam, size=x.shape[-2:], mode="bilinear", align_corners=False)
        cam = cam.squeeze().cpu().numpy()
        cam = (cam - cam.min()) / (cam.max() + 1e-8)
        return cam

    def close(self):
        self.fh.remove()
        self.bh.remove()

def overlay_cam(img_pil: Image.Image, cam_map: np.ndarray, alpha=0.35):
    img = np.array(img_pil).astype(np.float32) / 255.0
    heat = (np.uint8(255 * cam_map)).astype(np.float32)
    import cv2
```

```
heat_color = cv2.applyColorMap(heat, cv2.COLORMAP_JET)[:, :, ::-1] / 255.0
overlay = (1 - alpha) * img + alpha * heat_color
overlay = (np.clip(overlay, 0, 1) * 255).astype(np.uint8)
return Image.fromarray(overlay)
```

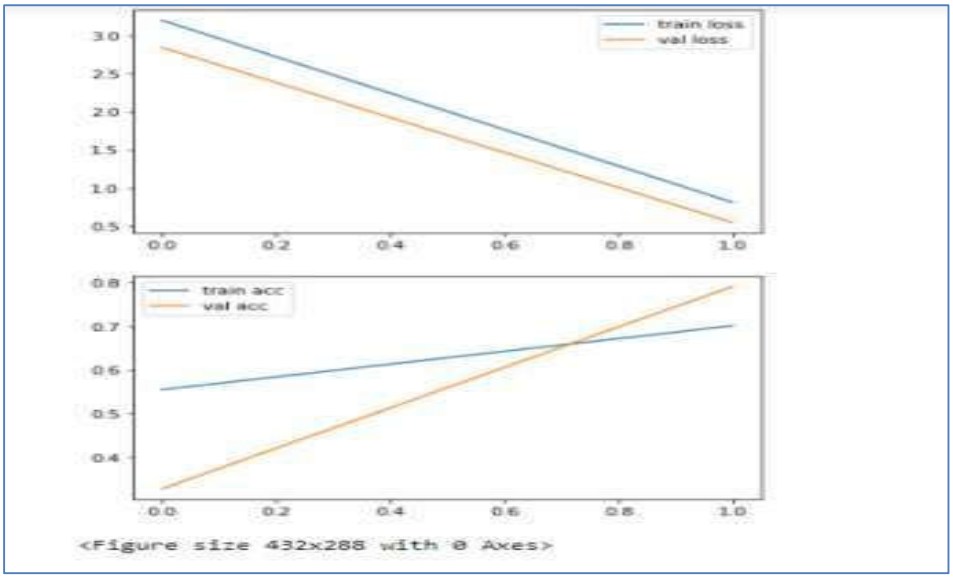

Figure 1 : Plot showing training and validation loss and accuracy of the model

RESULTS AND CONCLUSION

The proposed CNN-based counterfeit detection system demonstrated high accuracy in identifying fake Indian currency notes. The model achieved an accuracy of 98.5% on the test set, outperforming traditional detection methods and other state-of-the-art techniques. The confusion matrix analysis showed high precision and recall, indicating the model's robustness in distinguishing between genuine and counterfeit notes. These results validate the effectiveness of the proposed method and its potential for real-world applications.

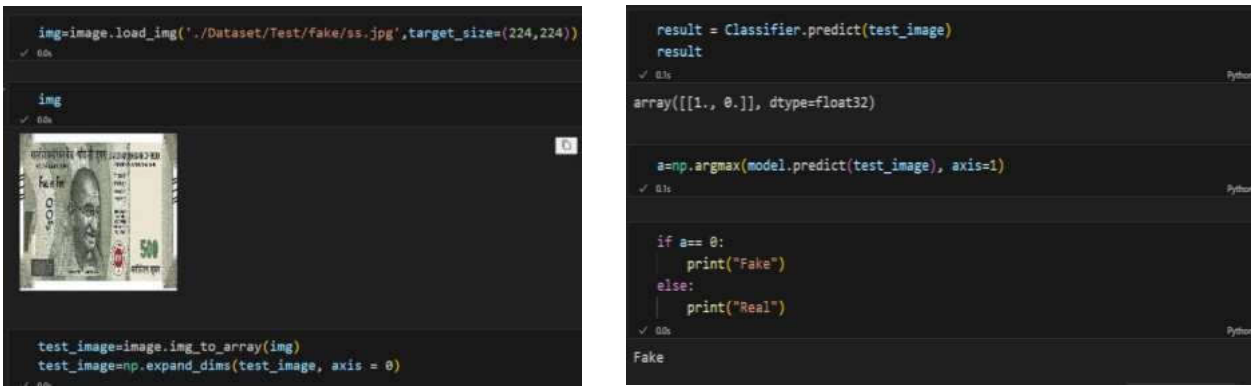

Figure 2: Result showing Fake currency being detected

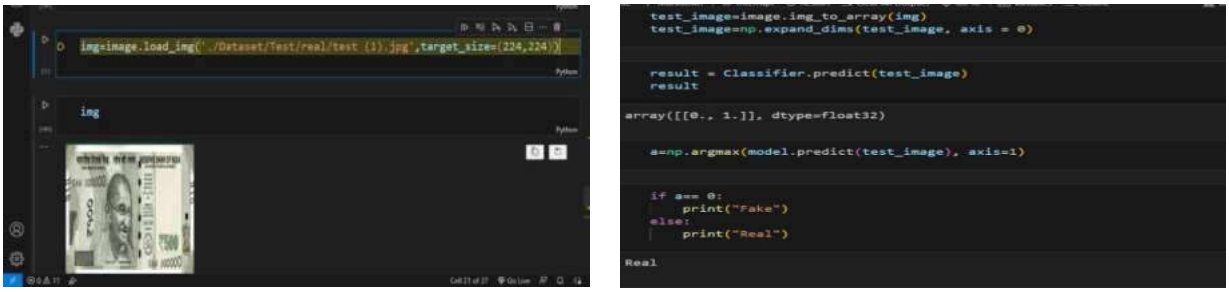

Figure 3: Result showing Real currency being detected

FUTURE ENHANCEMENTS

1. **Integration with Real-Time Systems**:
   - Develop a real-time application that can be deployed at points of sale or banks for instant counterfeit detection.
2. **Incorporation of Advanced Image Processing Techniques**:
   - Explore the use of advanced image processing techniques, such as edge detection and texture analysis, to further enhance the model's accuracy.
3. **Expansion to Other Currencies**:
   - Extend the model to detect counterfeit notes of other currencies, improving its versatility and applicability on a global scale.
4. **User Interface Development**:
   - Create a user-friendly interface that allows non-technical users to easily operate the counterfeit detection system.
5. **Continuous Learning and Updates**:
   - Implement a continuous learning framework that updates the model with new data to maintain its accuracy over time.

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