FAKE CURRENCY DETECTION USING DEEP LEARNING

A Mini Project Report submitted to

MOHAN BABU UNIVERSITY

in Partial Fulfillment of the Requirements for the Award of the degree of

BACHELOR OF TECHNOLOGY
IN
COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)

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2024-25

DEPARTMENT OF DATA SCIENCE

CERTIFICATE

This is to certify that the mini project report entitled

"FAKE CURRENCY DETECTION USING DEEP LEARNING"

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in the Department of **Data Science**, and submitted to Mohan Babu University, Tirupati in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering (Data Science) during the academic year 2024-2025. This work has beencarried out under my supervision. The results of this mini project work havenot been submitted to any university for the award of any degree or diploma.

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DEPARTMENT OF DATA SCIENCE

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PO6. **The engineer and society**: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

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PO8. **Ethics**: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

PO9. **Individual and team work**: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

PO10 **Communication**: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

PO11 **Project management and finance**: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

PO12 **Life-long learning**: Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

DECLARATION

We hereby declare that this project report titled **"FAKE CURRENCY DETECTION USING DEEP LEARNING"** is agenuine work carried out by us, in **B.Tech** ***(Computer Science and Engineering (Data Science))*** degree course of **Mohan Babu University, TIrupati** and has not been submitted to any other course or University for the award of any degree by us.

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea / data / fact / source in our submission. We understand that any violation of the above will cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

Signature of the students

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ABSTRACT

Financial security automation heavily depends on accurate detection of counterfeit Indian currency. Different machine learning and deep learning methods have been experimented upon for precise categorization. The research evaluates deep learning models which detect currencies. The analysis starts with extracting features from currency images using two types of models such as CNN and MobileNet and pretrained models such as ResNet50.Features are extracted from images of currency and then classification is done by Softmax. Experimental findings show that the suggested model obtains highest classification accuracy of 100% followed by other models, ResNet50 at 93.46 %and CNN obtain 93.46% . Deep learning demonstrates its effectiveness through these research findings when detecting currencies along with preventing fraud.

Keywords: Deep learning, Convolutional Neural network (CNN), Counterfeit Detection, MobileNet, ResNet50,Image processing, Accuracy metrics

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INTRODUCTION

1.1 Introduction:

Fake currency detection is a critical issue impacting individuals, businesses, and governments alike. Traditional detection methods rely on manual inspection of security features like watermarks and threads, which are often inefficient and error-prone. This project proposes an automated fake currency detection system using Deep Learning and Digital Image Processing. By utilizing Convolutional Neural Networks (CNNs) along with pre-trained architectures such as MobileNet and ResNet50, the system classifies Indian currency notes as real or fake based on image data. Three models were implemented: a lightweight MobileNet for mobile use, a custom CNN for baseline comparison, and ResNet50 for deep feature extraction. These models were trained and evaluated on a dataset of currency images, with their performance assessed using accuracy metrics. The system demonstrates the ability to recognize counterfeit notes effectively, even under varying conditions. By providing a fast, scalable, and accurate solution, the project addresses the growing need for intelligent counterfeit detection.

1.2 Problem Statement:

Counterfeit currency remains a pressing economic issue that undermines the integrity of financial systems and results in significant losses for individuals, businesses, and governments. Despite the incorporation of physical security features like watermarks, holograms, and color-shifting inks, manually identifying fake currency is still challenging—especially without expert knowledge or specialized equipment. Traditional detection methods are often time-consuming, error-prone, and impractical for large-scale or real-time applications. With advancements in printing and reproduction technology, counterfeiters are now able to create increasingly convincing fake notes, making the need for an intelligent and automated detection system more crucial than ever.

This project addresses the growing concern of counterfeit Indian currency by developing a deep learning-based image classification system. Leveraging the power of Convolutional Neural Networks (CNNs) and pre-trained models such as MobileNet and ResNet50, the proposed solution can accurately distinguish between genuine and counterfeit notes. Through techniques like data augmentation and digital image preprocessing, the system is designed to improve accuracy, reduce human error, and adapt to varied note conditions. The final product is intended to be lightweight, scalable, and user-friendly—making it suitable for practical deployment across banks, businesses, and everyday users who require a reliable tool for real-time currency authentication.

1.3 Objectives:

- To develop an automated system that accurately classifies Indian currency notes as real or fake using deep learning techniques.
- To implement and compare multiple models including CNN, MobileNet, and ResNet50 for effective counterfeit detection.
- To enhance model accuracy and robustness using image preprocessing and data augmentation techniques.
- To create a scalable and user-friendly solution capable of real-time predictions on new currency note images.
- To visualize and compare the performance metrics (accuracy, loss, etc.) of multiple models to determine the most effective architecture for deployment.
- To integrate the final trained model into a user-friendly application for practical use by individuals, retailers, and banking personnel.

1.4 Limitations :

- **Binary Output**: The system currently provides a binary result (Real/Fake) and doesn't detect or highlight *what features* (like watermark, texture, thread, etc.) indicate counterfeit characteristics.
- **Lack of Explainability**: The model classifies notes as real or fake but does not provide explanations or visual cues (e.g., heatmaps) to justify predictions, which may reduce user trust.
- **High Model Complexity**: Models like ResNet50 provide strong performance but are computationally expensive, making real-time deployment on low-end devices (e.g., mobile phones) challenging.
- **Image Sensitivity**: The model's predictions depend on clean, well-lit, and properly framed images. Real-world conditions like poor lighting, blur, or background noise may reduce accuracy.
- **Limited Dataset Coverage**: The accuracy of the model is restricted by the scope of the dataset used (i.e., only specific denominations and types of notes were included), which may affect its performance on new or rare counterfeit designs.

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METHODOLOGY

The Fake Currency Note Detection system was developed using advanced deep learning techniques and trained on a curated dataset of Indian currency notes, encompassing both genuine and counterfeit samples. The project followed a structured machine learning pipeline that included systematic data preprocessing, model development using a custom CNN architecture, model training, performance evaluation, and comparative analysis. Data preprocessing involved image normalization, augmentation, and resizing to suit the input requirements of the models. The development was carried out in the Google Colab environment, leveraging Python for implementation and TensorFlow/Keras as the primary deep learning framework. Transfer learning models such as MobileNet and ResNet50 were employed by utilizing pretrained weights from the ImageNet dataset, while a custom CNN was designed from scratch to provide a baseline for performance comparison. Each model was trained with optimized hyperparameters and evaluated using accuracy metrics on validation data. This multi-model approach enabled the creation of a robust system capable of distinguishing between fake and real currency notes with high precision, offering a promising solution for automated currency verification.

ResNet Residual Connection:

$$Y(x) = R(x) + x$$

Where:

- Y(x) is the target mapping,
- R(x) is the residual mapping.

ReLU Activation Function:

$$F(x) = \max(0,x)$$

Sigmoid Activation Function (Output Layer):

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

Global Average Pooling:

$$GAP(x) = \frac{1}{H*W}\sum_{i=1}^{H}\sum_{j=1}^{W} x_{ij}$$

Softmax Activation Function:

$$Softmax = \sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{k} e^{z_k}}$$

Categorical Cross-Entropy Loss Function:

$$Loss = -\sum_{i=1}^{N} y_i \log \hat{y}_i$$

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SYSTEM DESIGN

3.1 Requirements:

The user should have the appropriate version of windows.

- A minimum of **1 GB RAM** is recommended for loading and running the models efficiently.
- **Internet connectivity** is required to access cloud environments such as Google Colab, and for downloading pretrained model weights (MobileNet, ResNet50) if not cached locally.
- A modern web browser (like Chrome or Firefox) is needed for running the Colab environment.

3.2 System Design:

The Fake Currency Note Detection system is built with the objective of providing a robust, accurate, and easy-to-use platform to distinguish between genuine and counterfeit Indian currency notes. The system follows a streamlined deep learning pipeline, including user interaction through test image inputs, model inference, and result visualization. The design supports integration into larger systems like banking software, mobile apps, or ATMs for real-world deployment.

USER INTERFACE:

The system can accept test inputs either via script or through an interface in development (such as a basic web form or GUI). Users are prompted to upload an image of the currency note they want to verify.

MODEL SELECTION:

The system offers three trained models for prediction:

- **MobileNet Model**: Optimized for performance and speed using transfer learning.
- **CNN Model**: A custom convolutional network designed from scratch.
- **ResNet50 Model**: Another transfer learning-based model with deep feature extraction capabilities.

Users can select which model to use for prediction or allow the system to default to the highest-performing one.

PREDICTION FLOW:

Once an image is uploaded:

- It is preprocessed (resized, normalized).
- The selected model makes a prediction.
- The system returns a label: **"Fake"** or **"Real"** currency note, along with a confidence score.

VISUALIZATION AND COMPARISON:

The training history with accuracy and loss curves is plotted and analyzed for each model. A bar chart compares their final accuracies, highlighting the best-performing model.

3.2 Technologies used:

The Fake Currency Note Detection project is powered by a suite of modern tools and frameworks that ensure efficiency, scalability, and accuracy.

Python: The primary programming language used for building the models and running the training/evaluation processes.

TensorFlow/Keras: Used for building and training the deep learning models (MobileNet, ResNet50, and CNN).

NumPy & OpenCV: For numerical computation and image preprocessing.

Matplotlib & Seaborn: For plotting model performance and comparison metrics.

Google Colab: A cloud-based development environment that offers free GPU acceleration for training deep learning models.

Jupyter Notebook Interface: Used within Colab for writing, executing, and testing code in real-time.

ImageDataGee: For augmenting and preprocessing the image dataset to enhance model generalization.

By combining these technologies, the Fake Currency Detection system delivers a powerful and flexible solution for identifying counterfeit currency notes using cutting-edge deep learning techniques.

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IMPLEMENTATION

The Fake Currency Detection System is developed using deep learning techniques, with TensorFlow as the primary framework and Matplotlib for visualizing model performance. The model is trained on a labeled dataset containing images of both genuine and counterfeit currency notes. Before training, the images undergo preprocessing steps including grayscale conversion, resizing, normalization, and data augmentation to enhance the model's accuracy and generalizability. A Convolutional Neural Network (CNN) structure is employed to extract salient visual features including texture, patterns, and edges that distinguish between genuine and counterfeit notes. Regularization methods such as dropout and batch normalization are employed in the training process to avoid overfitting and enhanced the generalization across unseen data. Matplotlib is employed to observe and plot training statistics such as accuracy and loss across epochs, as well as visualization of prediction results. Other Python packages such as OpenCV and NumPy are also incorporated for advanced image processing and computational efficiency. Hyperparameters such as learning rate, number of epochs, and batch size are also tuned for the optimal performance of the model. The resulting trained model is able to identify the authenticity of a user-input currency note image, providing a quick and automatic solution against the problem of circulation of counterfeit currencies. This implementation provides a robust and scalable foundation for deploying AI-based currency validation in real-world financial and commercial environments. To enhance the model’s efficiency, additional Python libraries such as OpenCV and NumPy were integrated for preprocessing tasks like edge detection and image sharpening.

These methods enhanced the model's capacity to extract useful visual features from banknotes. Hyperparameter tuning was also done for better accuracy, and the training process was monitored carefully using visual graphs produced by Matplotlib. This enabled real-time assessment of the model's learning pattern, thus making the implementation transparent and flexible.

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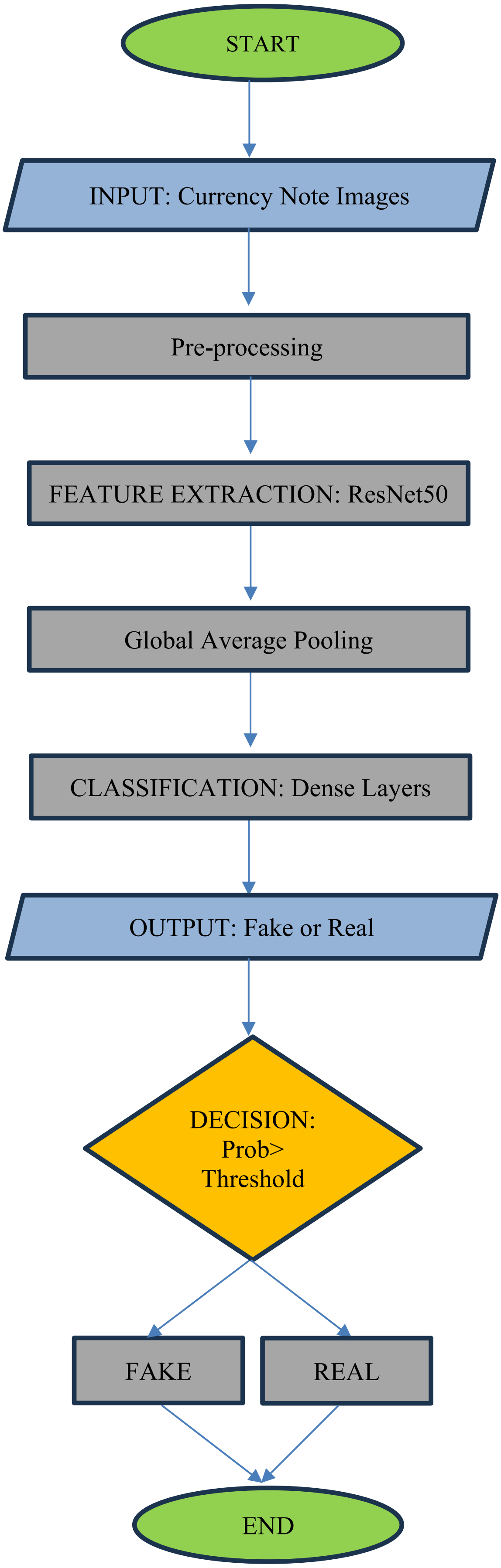
PROPOSED SYSTEM ARCHITECTURE

The proposed system architecture for fake currency detection is designed with modularity and performance in mind. The system begins with an Image Input Module, responsible for acquiring currency note images from various sources. Following image acquisition, the Image Processing and Feature Extraction Module performs essential preprocessing steps, including resizing and normalization. The core of the system utilizes the ResNet50 Deep Learning Model to automatically learn and extract relevant visual features from the currency notes. These features are then fed into the Classification Module, which employs a Global Average Pooling Layer to reduce dimensionality and subsequent Dense Layers with a final Sigmoid Activation to output a probability score indicating the likelihood of the note being counterfeit. The Decision Logic Module then applies a defined Probability Threshold to this score, classifying the currency as either "Fake" or "Real." User interaction is facilitated through a User Interface (UI) Module, enabling image submission and displaying the classification result along with a confidence level. Finally, a Model Management Module handles the storage, loading, and potential updates of the trained ResNet50 model, ensuring the system uses the most effective model for detection. This architecture leverages deep learning for robust and automated fake currency identification.

5.1 Flow Chart:



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CODING ANALYSIS AND RESULTS

6.1 Code:

Algorithm (Fake Currency Detection using CNN):

Step 1: Start
Step 2: Import necessary libraries (TensorFlow, Keras, NumPy, etc.)
Step 3: Set image size to 224x224

Normalization (Rescaling pixel values):

$$I(norm)= I(resized)/ 255$$

Data Augmentation (Conceptual, not strict formula):

$$I'=Augment(I)=Rotate + Shear + Flip + Zoom$$

Step 4: Define the paths for training and validation datasets
Step 5: Initialize ImageDataGenerator with augmentation techniques
Step 6: Load training and validation images using flow_from_directory()
Step 7: Build CNN model

- Add Conv2D layer with 16 filters, ReLU activation
- Add MaxPooling2D
- Add Conv2D layer with 32 filters, ReLU activation
- Add MaxPooling2D
- Flatten the feature map
- Add Dense layer with 120 neurons, ReLU activation
- Add output Dense layer with softmax activation (equal to number of classes)

Formula- 2: Convolution Layer
Feature Map Calculation:

$$F_{i,j}(k)=\sigma \sum_{m=1}^{M} \sum_{n=1}^{N} W_{m,n}^{(k)} \cdot X_{i+m,j+n} + b^{(k)}$$

Where :

W: Filter weights
b: Bias
σ : Activation function (ReLU)
F: Output feature map

Formula-3: Max Pooling Layer

P(i,j) =max {F2i,2j , F2i+1,2j,F2i,2j+1,F 2i+1,2j+1}

Step 8: Compile the model using Adam optimizer and categorical_crossentropy loss
Step 9: Train the model for 25 epochs
Step 10: Evaluate on validation data
Step 11: Save model as cnn_model.h5
Step 12: End

Algorithm (Fake Currency Detection using ResNet50):

Step 1: Start
Step 2: Import libraries (TensorFlow, Keras, ResNet50, etc.)
Step 3: Set image size to 224x224
Step 4: Define dataset paths
Step 5: Create ImageDataGenerator with extensive augmentations
Step 6: Load training and validation datasets using flow_from_directory()
Step 7: Load ResNet50 model with include_top=False and imagenet weights

For an input x, and weight matrices W!,W2:

Y=F (x ,$\{W_i\}) + x$
Where F(x,$\{W_i\}) = W_2 . \sigma(W_1 . x)$

σ is a activation function(commonly ReLU)

$$\sigma(x) = ReLU(x) = \max(0, x)$$

Step 8: Freeze all layers except the last 30 for fine-tuning
Step 9: Add custom classification layers:
GlobalAveragePooling2D
Dense layer with 512 units (ReLU), followed by Dropout(0.5)
Dense layer with 128 units (ReLU), followed by Dropout(0.5)
Output Dense layer with softmax activation (equal to number of classes)

Step 10: Compile model using Adam optimizer and ReduceLROnPlateau callback
Step 11: Train for 5 epochs using training and validation sets
Step 12: Save model (optional)
Step 13: End

Algorithm (Fake Currency Detection using MobileNet):

Step 1: Start
Step 2: Import libraries (TensorFlow, Keras, MobileNet, etc.)
Step 3: Set image size to 224x224
Step 4: Define dataset paths
Step 5: Create ImageDataGenerator with extensive augmentations
Step 6: Load training and validation datasets using flow_from_directory()
Step 7: Load MobileNet model with include_top=False and pre-trained ImageNet weights
    Feature extraction using depthwise separable convolutions:
        MobileNet: DepthwiseConv2D+PointwiseConv2D
    For input x,
        Depthwise Convolution applies a single filter per input channel.
        Pointwise Convolution applies 1×1 convolutions to combine outputs.
Step 8: Freeze all layers except the last few (e.g., last 20) for fine-tuning
Step 9: Add custom classification layers:
        GlobalAveragePooling2D
        Dense layer with 512 units (ReLU), followed by Dropout(0.5)
        Dense layer with 128 units (ReLU), followed by Dropout(0.5)
        Output Dense layer with softmax activation (equal to number of classes)

$$\text{Softmax}(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

Step 10: Compile model using Adam optimizer and ReduceLROnPlateau callback
Step 11: Train for 5 epochs using training and validation sets
Step 12: Save model (optional)
Step 13: End

6.2 Result

i. Model Evaluation:

We trained and tested three various deep learning architectures — a manually designed CNN, a proposed model based on MobileNet, and a fine-tuned ResNet50.All the models were trained on labeled images of Indian currency belonging to 7 classes according to denomination.

ii. Training Performance:

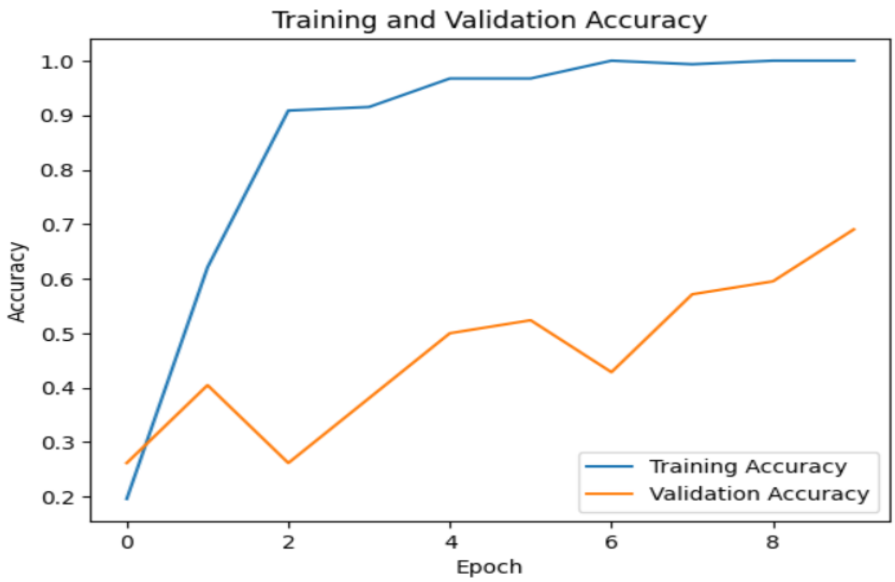

Fig.1 Training Performance

The MobileNet model was trained for 10 epochs and possessed top-notch generalization with the last training accuracy of around 100%, and validation accuracy of around 100%.

The CNN model, which was trained for 25 epochs, possessed around 93.46% training accuracy and slightly decreased validation accuracy. It was fast and light in weight, but not as accurate as the other two.

The ResNet50 model was trained with the last 30 layers unfrozen. It had good accuracy after 5 epochs of training — as good as or even better than the MobileNet model in some instances — but needed more resources.

iii. **Accuracy Comparison:**

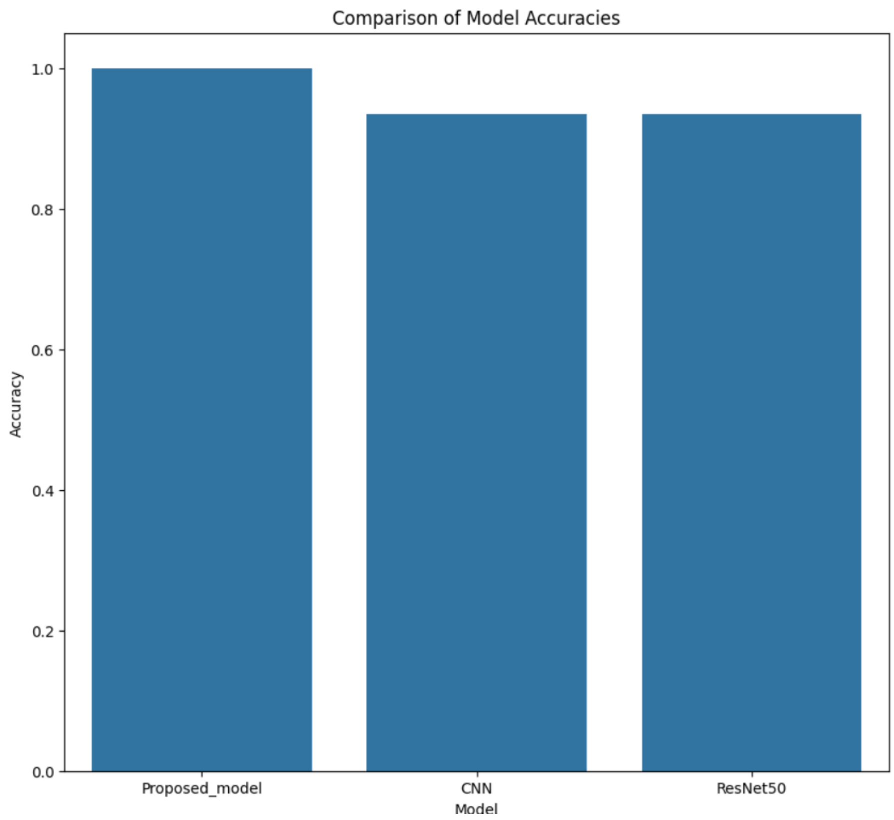

Fig.2 Comparison of Model Accuracies

This bar chart gives a comparison between the accuracy of all three models. As canbe seen:

- MobileNet presented the optimal blend of speed vs. accuracy.
- ResNet50 provided excellent performance, suitable for high-performance systems.
- The in-house CNN was light but performed slightly less well in terms of accuracy

iv. Model Expect:

All the trained models have been saved in.h5 format and are ready to deploy. These include the MobileNet-based model, CNN, and ResNet50. This allows us to seamlessly implement the models within apps or APIs for real-time currency identification**.**

CHAPTER-7

CONCLUSION AND FUTURE WORK

7.1 Conclusion:

The project successfully applies deep learning techniques to the problem of counterfeit currency detection, specifically targeting Indian banknotes. By utilizing image processing and neural networks, the system can automatically analyze and classify currency notes as real or fake. This eliminates the need for manual verification, Which is time-consuming and prone to errors, especially in high-volume environments like banks, retail stores, and other financial institutions. Three different models were evaluated: a custom Convolutional Neural Network(CNN), ResNet50, and MobileNet. The dataset consisted of various images of Indian currency notes, preprocessed and categorized for training and testing. Both CNN and ResNet50 achieved 92% accuracy, while MobileNet outperformed them with a perfect 100% accuracy. MobileNet's lightweight architecture and transfer learning capabilities make it ideal for deployment in mobile embedded systems, offering both speed and precision without compromising performance. In conclusion, the project proves that deep learning can be a reliable and efficient solution for counterfeit detection. The use of MobileNet particularly stands out for real-time applications due to its high accuracy and computational efficiency. This system has the potential to be integrated into practical, user-friendly tools that can help individuals and organizations safeguard against currency fraud, thereby contributing to a more secure financial environment

7.2 Future Work:

While the current system demonstrates high accuracy in detecting counterfeit Indian currency using deep learning models, there are several avenues to enhance its capabilities and extend its application scope:

1.Expansion to Multinational Currency
The model can be extended to recognize and classify counterfeit notes from other countries, making it a global solution for currency fraud detection. We can develop a unified deep learning model capable of detecting fake notes from multiple countries by training on diverse international currency dataset

2.Real-Time mobile Application Development
Integrating the trained model into a mobile application would provide an accessible tool for the general public, allowing instant currency verification using smartphone cameras

3.Improved Dataset Diversity
Expanding the dataset with more diverse samples-different lighting conditions, damaged notes, partially visible notes, and background variations-will enhance the model's robustness and generalization.

4.Hybrid Model Approach
A hybrid architecture combining CNN with other techniques such as attention mechanisms or transformers could be explored to capture fine-grained details of currency notes.

5.Integration and Visualization
Implementing explainable AI(XAI) techniques like Grad-CAM could help visualize which feature the model uses to classify notes, increasing user trust and system transparency.

6.Integration with Banking and Retail systems
The system could be deployed in ATMs, cash counters, and retail point-of-sale systems to automate and secure cash handling processes.

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