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CURRENCY RECOGNITION WITH DEEP LEARNING TECHIQUES

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ABSTRACT
This project focuses on developing a deep learning–based model using Convolutional Networks (CNNs) for accurate and efficient Indian paper currency recognition, which significantly aids visually impaired individuals. By training a Keras deep learning model and deploying it through a Flask-based web application on Heroku, the system ensures reliable, high-speed, and automatic currency identification with minimal complexity. This approach enhances accessibility and inclusivity while meeting modern technological needs.
Keywords:
Indian Currency Recognition, CNN, Deep Learning, Computer Vision, Assistive Technology.

1. Introduction

In recent years, automation and intelligent systems have significantly transformed various aspects of everyday life. The integration of artificial intelligence and machine learning techniques has enabled machines to perform complex tasks such as image classification, speech recognition, and object detection with high efficiency.

Currency recognition is an important application of computer vision that plays a crucial role in financial systems, vending machines, and automated teller machines. Manual identification of currency notes can be time-consuming and error-prone, especially when notes are damaged, folded, or worn out. The problem becomes even more critical for visually impaired individuals who rely heavily on external assistance for identifying different currency denominations.

India uses multiple currency denominations such as ₹10, ₹20, ₹50, ₹100, ₹200, ₹500, and ₹2000. Due to similarities in note dimensions and designs, identifying these denominations without visual assistance can be challenging.

To address these challenges, this research proposes a **deep learning–based Indian currency recognition system** using Convolutional Neural Networks (CNN). Deep learning models automatically learn distinctive features from images, making them highly suitable for currency classification tasks.

The proposed system utilizes a CNN model developed using the Keras framework and integrates it into a Flask web application. The system allows users to upload an image of a currency note, after which the model predicts the denomination and displays a confidence score. This approach provides a reliable and user-friendly solution that enhances accessibility and independence for visually impaired individuals.

2. Literature Review

Numerous research studies have explored different techniques for automatic currency recognition. Early approaches primarily relied on image processing methods such as edge detection, color analysis, and pattern matching.

Kamal et al. (2015) proposed a feature extraction method for identifying Indian currency notes using image processing techniques. Their system focused on extracting key features such as textures and patterns from currency images to distinguish between denominations.

Sarfraz (2015) developed an intelligent currency recognition system based on machine learning algorithms. The proposed approach aimed to improve the accuracy of recognition by incorporating multiple feature extraction methods.

With the advancement of artificial intelligence, deep learning techniques have become increasingly popular for image recognition tasks. **Zhang et al. (2019)** presented an overview of deep learning-based currency recognition systems and demonstrated that Convolutional Neural Networks significantly outperform traditional machine learning models in image classification tasks.

Recent studies have also explored transfer learning models such as VGG16 and ResNet for currency recognition. These models utilize pre-trained neural networks to improve classification accuracy while reducing training time.

Although existing research has shown promising results, several challenges remain, including poor performance under varying lighting conditions, recognition of damaged notes, and the need for large training datasets. The proposed system aims to overcome these limitations by using an optimized CNN architecture and extensive data augmentation techniques.

3. Existing System

3.1 Overview of Existing Systems

Traditional currency recognition systems rely on manual inspection or basic image processing techniques. Some automated systems use ultraviolet (UV) detection to verify security features embedded in currency notes. While these systems provide a certain level of reliability, they may fail when dealing with highly sophisticated counterfeit notes.

Earlier research also explored computer vision techniques using libraries such as OpenCV combined with machine learning algorithms. These systems typically extract handcrafted features from currency images and classify them using models such as Support Vector Machines (SVM) or Artificial Neural Networks (ANN).

Although these methods provide moderate accuracy, they often struggle with variations in lighting conditions, note orientation, and background noise.

3.2 Limitations of Existing Systems

Several limitations have been identified in existing currency recognition systems:

1. **Dependence on Dataset Quality**

Recognition accuracy heavily depends on the diversity and size of the dataset used for training.

2. **Requirement for Continuous Updates**

Currency designs and counterfeit techniques evolve over time, requiring regular updates to recognition models.

3. **Sensitivity to Environmental Conditions**

Recognition accuracy may decrease in poor lighting conditions or when notes are severely damaged.

4. **Computational Complexity**

Advanced machine learning models require substantial computational resources.

5. **Limited Generalization**

Systems trained for one country's currency may not recognize other currencies.

6. **Internet Dependency**

Web-based systems require stable internet connectivity for real-time recognition.

4. Proposed System

The proposed system introduces an intelligent currency recognition framework based on **deep learning and computer vision techniques**. The objective of this system is to accurately identify Indian currency denominations from input images while maintaining high reliability and efficiency. The system is particularly designed to assist visually impaired individuals and automate currency identification tasks in financial applications.

The proposed framework integrates **image preprocessing, feature extraction, classification, and web-based deployment** to provide a complete end-to-end recognition pipeline. A **Convolutional Neural Network (CNN)** model is utilized to automatically learn hierarchical visual features from currency images without requiring manual feature engineering.

The system is implemented using the **Keras deep learning library** and deployed through a **Flask web application**, enabling users to upload currency images through a web interface. The trained model analyzes the input image and predicts the corresponding currency denomination along with a confidence score.

The architecture of the proposed system consists of several interconnected modules that work collaboratively to achieve accurate recognition.

4.1 System Architecture

The proposed architecture follows a **multi-stage processing pipeline** consisting of the following major stages:

1. **Image Acquisition**
2. **Image Preprocessing**
3. **Feature Extraction using CNN**
4. **Currency Classification**
5. **Similarity Score Calculation**
6. **Result Visualization**
7. **Web Application Integration**

The system begins by accepting an image of a currency note uploaded by the user through the web interface. The uploaded image is then forwarded to the backend server where preprocessing and feature extraction operations are performed. The CNN model processes the image and predicts the denomination based on learned patterns and textures. Finally, the predicted result and confidence score are displayed to the user.

4.2 Image Acquisition

The first stage of the system involves acquiring images of Indian currency notes. Users can upload images captured using mobile phones or digital cameras through the web interface.

The system supports commonly used image formats such as:

- JPEG
- PNG
- JPG

The uploaded image is securely transmitted to the backend server for further processing.

To ensure reliable recognition, the dataset used for training includes images of different currency denominations under various conditions such as:

- Different lighting environments

- Various orientations and rotations
- Background variations
- Old, folded, or partially damaged notes

These variations improve the robustness of the trained deep learning model.

4.3 Image Preprocessing

Image preprocessing is an essential step that prepares the input data before it is fed into the CNN model. The primary objective of preprocessing is to enhance image quality and standardize the input format.

The following preprocessing operations are performed:

Image Resizing

All input images are resized to a fixed dimension compatible with the CNN input layer. This ensures uniformity across the dataset and reduces computational complexity.

Pixel Normalization

Pixel values are normalized to a range between **0 and 1**, which improves training stability and accelerates convergence during model training.

Noise Reduction

Noise removal techniques are applied to reduce unwanted distortions that may affect recognition accuracy.

Data Augmentation

To improve the generalization ability of the model, several data augmentation techniques are applied during training:

- Rotation
- Horizontal flipping
- Scaling
- Brightness adjustments

These techniques artificially expand the dataset and reduce the risk of overfitting.

4.4 Feature Extraction Using CNN

Feature extraction is performed using a **Convolutional Neural Network**, which is specifically designed for image classification tasks.

CNNs automatically learn relevant visual features such as:

- Edges
- Textures
- Patterns
- Shapes
- Security features of currency notes

The CNN architecture used in the proposed system consists of multiple layers:

Convolution Layers

These layers apply convolution filters to the input image to detect local patterns and important visual features.

Activation Function (ReLU)

The **Rectified Linear Unit (ReLU)** activation function introduces non-linearity into the network and improves training efficiency.

Pooling Layers

Pooling layers reduce the spatial dimensions of feature maps while preserving important information. This reduces computational cost and prevents overfitting.

Dropout Layers

Dropout layers randomly deactivate neurons during training to improve generalization and reduce overfitting.

Fully Connected Layers

The extracted features are flattened and passed to fully connected layers, which perform the final classification of the currency denomination.

4.5 Currency Classification

Once features are extracted by the CNN layers, the classification stage determines the denomination of the currency note.

The classifier outputs probability values for each denomination class. The class with the highest probability is selected as the predicted currency denomination.

For example, the model may classify the note as:

- ₹10
- ₹20
- ₹50
- ₹100
- ₹200
- ₹500
- ₹2000

The classification process is performed in real time once the trained model receives an input image.

4.6 Similarity Score Calculation

In addition to predicting the currency denomination, the system also calculates a **similarity score (confidence score)**.

This score represents the probability associated with the predicted class and helps validate the reliability of the prediction.

For instance:

Currency	Confidence Score
₹500	98.7%
₹200	1.1%
₹100	0.2%

The highest probability value is considered the final prediction.

Providing this confidence score improves transparency and reliability of the system.

4.7 Web Application Integration

To make the system accessible and user-friendly, the trained CNN model is integrated into a web application developed using the **Flask framework**.

The web application performs the following functions:

- Accepts image uploads from users
- Sends images to the backend server
- Performs preprocessing and prediction
- Displays recognition results to users

The web interface is developed using:

- HTML
- CSS
- JavaScript

Security features such as **CSRF protection** are implemented to prevent unauthorized requests.

4.8 Deployment

The complete system is deployed on a cloud platform to allow remote access through a web browser.

The deployment environment includes:

- Flask web server
- Deep learning model integration
- Cloud hosting platform

This deployment approach enables users to access the currency recognition system from any device with internet connectivity.

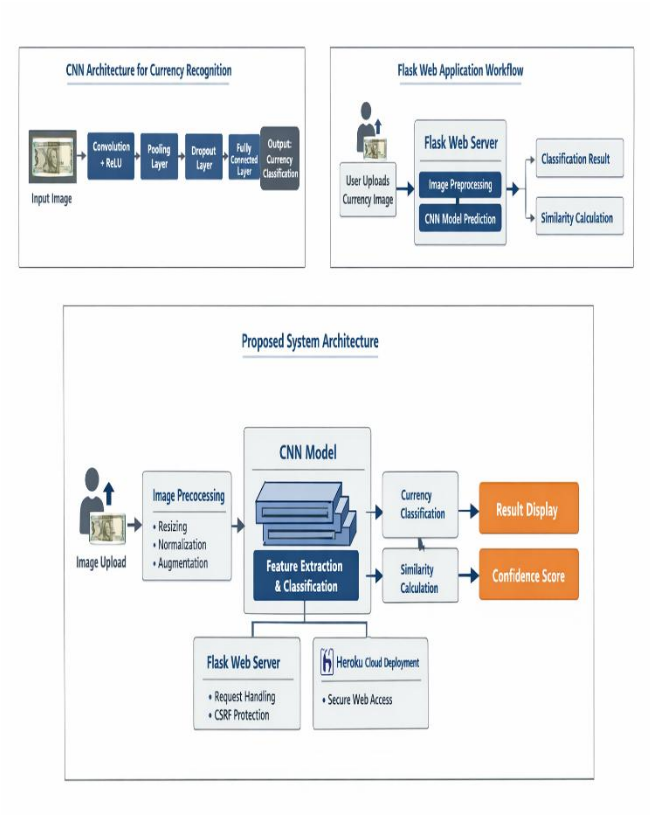


Fig 4.1 : Currency recognition system architecture

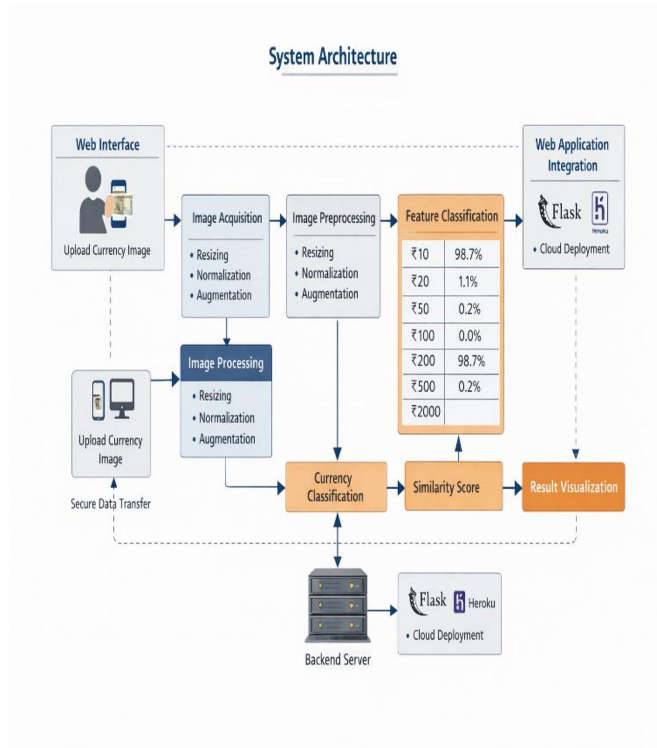


Fig 4.2 : Indian currency recognition system

5. Methodology

The development of the proposed Indian currency recognition system follows a systematic methodology that integrates image processing techniques with deep learning-based classification. The methodology involves several stages including dataset preparation, preprocessing, model architecture design, training, evaluation, and prediction. Each stage plays a crucial role in improving the overall performance and reliability of the recognition system.

5.1 Data Collection

The first stage of the methodology involves collecting a comprehensive dataset of Indian currency note images representing different denominations. Images were gathered from publicly available datasets, online repositories, and image collections to ensure sufficient diversity.

The dataset includes various denominations such as:

- ₹10
- ₹20
- ₹50
- ₹100
- ₹200
- ₹500
- ₹2000

To enhance the robustness of the model, the dataset contains images captured under different environmental conditions. These variations include differences in lighting conditions, orientations, backgrounds, and note quality such as folded, wrinkled, or partially damaged currency notes.

A diverse dataset is essential for training the CNN model to recognize complex visual patterns and generalize effectively to unseen images.

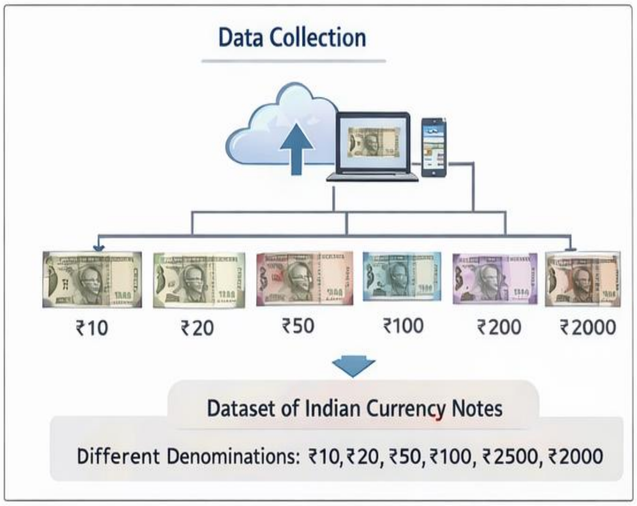


Fig 5.1 Data Collection

5.2 Data Preprocessing

Data preprocessing is an essential step that prepares raw input images before they are provided to the deep learning model. The primary objective of preprocessing is to standardize image inputs and enhance important visual features that contribute to accurate classification.

Several preprocessing techniques are applied in this stage:

Image Resizing

All images are resized to a fixed resolution that matches the input dimensions required by the CNN model. Standardizing image size ensures consistent input representation and reduces computational complexity during training.

Pixel Normalization

Pixel intensity values are normalized to a range between **0 and 1** by dividing the pixel values by 255. This normalization improves numerical stability and accelerates the learning process during training.

Noise Reduction

Noise and unwanted distortions present in the images are minimized using filtering techniques. This helps preserve important features of the currency notes while removing irrelevant background artifacts.

Data Augmentation

To improve the generalization capability of the model and prevent overfitting, various data augmentation techniques are applied to artificially increase the size of the dataset. These techniques include:

- Image rotation
- Horizontal flipping
- Scaling and zooming
- Brightness adjustments

Data augmentation allows the model to learn from multiple variations of the same image, making it more robust to real-world conditions.

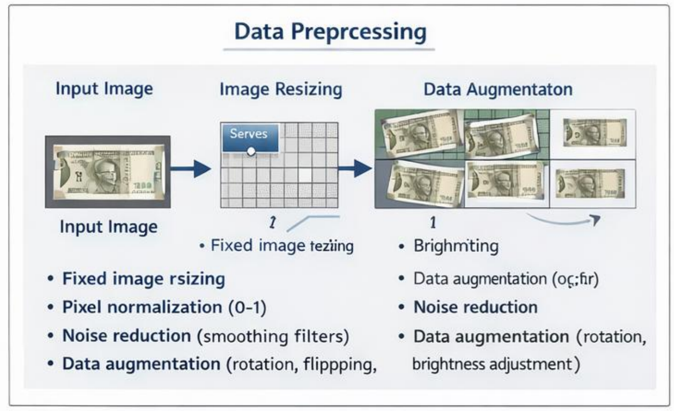


Fig 5.2 Data Collection

5.3 Model Design (CNN Architecture)

The core component of the proposed system is a **Convolutional Neural Network (CNN)** designed for automatic feature extraction and classification of currency images.

CNNs are highly effective for image recognition tasks because they can automatically learn hierarchical features from input images without requiring manual feature engineering.

The architecture of the CNN model consists of several layers:

Convolutional Layers

Convolutional layers apply multiple filters to the input images in order to extract low-level and high-level visual features such as edges, shapes, and texture patterns present in currency notes.

Activation Function (ReLU)

The **Rectified Linear Unit (ReLU)** activation function introduces non-linearity into the model, enabling the network to learn complex relationships between input images and output classes.

Pooling Layers

Pooling layers perform dimensionality reduction by selecting the most prominent features from the convolutional feature maps. This reduces computational cost and helps prevent overfitting.

Dropout Layers

Dropout layers randomly deactivate certain neurons during training to reduce overfitting and improve the model's ability to generalize to unseen data.

Fully Connected Layers

The final stage of the CNN architecture consists of fully connected layers that combine the extracted features and perform classification into predefined currency denomination classes.

5.4 Model Training and Validation

After designing the CNN architecture, the model is trained using the prepared dataset. The dataset is divided into two subsets:

- **Training dataset** – used to train the model

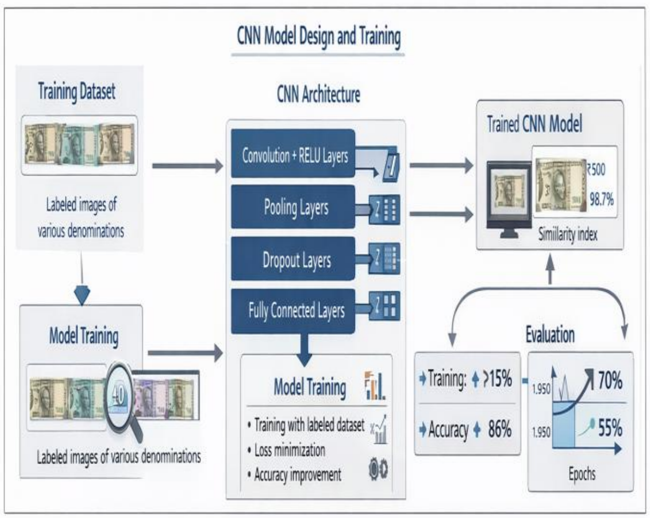
- **Validation dataset** – used to evaluate model performance during training

During the training process, the model learns to identify important visual features associated with different currency denominations. The optimization process adjusts the network weights iteratively using backpropagation and gradient descent algorithms.

To monitor the performance of the model, several evaluation metrics are used:

- Training accuracy
- Validation accuracy
- Training loss
- Validation loss

These metrics help determine whether the model is learning effectively and whether overfitting or underfitting is occurring.



5.5 Currency Recognition and Prediction

Once the CNN model has been successfully trained, it is used for predicting the denomination of new currency images. During this stage, an input image is passed through the trained network, which analyzes its features and assigns probability values to each currency class.

The class with the highest probability is selected as the predicted currency denomination.

For example:

Predicted Class	Probability
₹500	0.991
₹200	0.005
₹100	0.004

The predicted result is then displayed to the user along with the corresponding probability value.

5.6 Similarity Index and Validation

In addition to predicting the currency denomination, the system calculates a **similarity index**, also referred to as the confidence score. This value represents the likelihood that the predicted class is correct.

The similarity index helps validate the reliability of the prediction and allows users to understand the certainty level of the recognition result.

Providing a confidence score improves system transparency and helps users make informed decisions regarding the predicted currency denomination.

6. Results and Discussion

The performance of the proposed **Indian Currency Recognition System** was evaluated using a dataset consisting of images from different Indian currency denominations. The dataset included notes with variations in orientation, lighting conditions, background complexity, and physical condition of the notes. This diversity ensured that the trained model could generalize effectively to real-world scenarios.

The Convolutional Neural Network (CNN) model was trained using the preprocessed dataset, and its performance was evaluated based on classification accuracy, prediction confidence, and response time.

The experimental results demonstrate that the proposed deep learning model achieved an overall **classification accuracy of 99.14%**, indicating highly reliable currency recognition performance. The use of convolutional layers enabled the model to automatically extract significant visual features such as textures, edges, and security patterns present in currency notes.

The system was tested under multiple challenging conditions to evaluate its robustness. These conditions included:

- **Varying lighting environments** – Images captured under different illumination levels were successfully classified by the system.
- **Partially folded or wrinkled currency notes** – The CNN model could still detect important visual patterns despite distortions in the note structure.
- **Moderately damaged notes** – Even when the currency notes contained minor wear or damage, the model maintained high recognition accuracy.

The application was integrated into a **Flask-based web interface**, allowing users to upload images of currency notes through a browser. Once an image is uploaded, the system performs preprocessing, feature extraction, and classification in real time. The predicted denomination is displayed along with a **similarity (confidence) score**, which indicates the probability of the predicted class.

For example, a typical prediction output may appear as:

Currency Denomination	Confidence Score
₹500	98.7%
₹200	1.1%
₹100	0.2%

The highest probability value is selected as the final predicted denomination.

The inclusion of a confidence score enhances the reliability of the system by allowing users to understand how certain the model is about its prediction. This feature is particularly

useful when dealing with damaged or partially visible notes.
Furthermore, the deployment of the system using a **Flask web server** ensures fast response times and seamless interaction between the user interface and the deep learning model. The results demonstrate that the proposed system is capable of performing accurate currency recognition in real-time scenarios while maintaining high computational efficiency.
Overall, the experimental evaluation confirms that the proposed deep learning approach provides a robust and efficient solution for Indian currency recognition. The system not only improves automation in financial applications but also offers practical assistance to visually impaired individuals by enabling reliable currency identification.

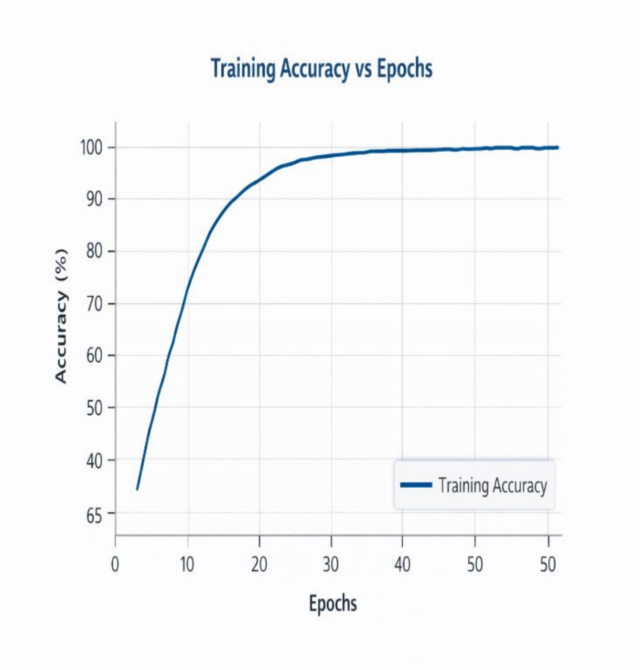


Figure 6.2 – Training Loss vs Epochs

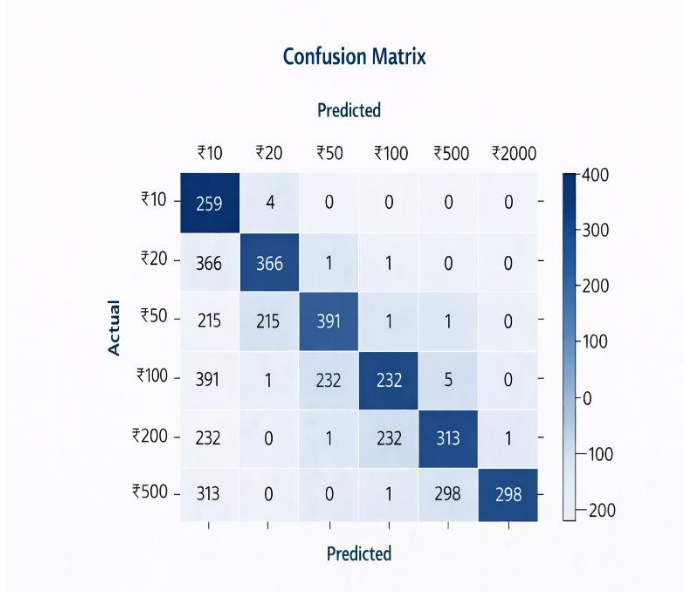


Figure 6.3 – Confusion Matrix

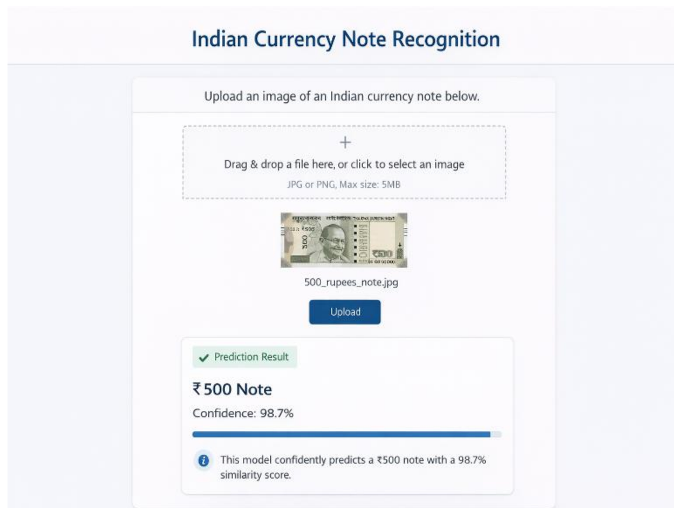


Figure 6.4 – Prediction Result Interface

7. Conclusion

This research presents a deep learning-based approach for the automatic recognition of Indian currency notes using a Convolutional Neural Network (CNN). The proposed system was designed to accurately identify different currency denominations from input images by utilizing advanced image processing and deep learning techniques. The integration of preprocessing methods such as image resizing, normalization, and data augmentation helped improve the quality of the dataset and enhanced the overall performance of the model.

The CNN architecture effectively extracted important visual features from currency images and achieved high accuracy in classification. The system was capable of recognizing currency notes even under variations in orientation, lighting conditions, and moderate damage. Furthermore, the deployment of the trained model through a

Flask-based web application enabled users to upload images and obtain recognition results quickly and efficiently.

The developed system can serve as a practical solution for currency identification and has potential applications in banking systems, automated machines, and assistive technologies. In particular, the system can significantly help visually impaired individuals by enabling them to easily identify different currency denominations.

Future Scope

Although the proposed system performs effectively, several improvements can be explored in future work. The system can be extended to support recognition of multiple international currencies by training the model with additional datasets. A mobile application version of the system can also be developed to allow users to identify currency notes using smartphone cameras.

Future research can also focus on implementing real-time recognition using live camera input instead of static images. Additionally, advanced techniques can be incorporated to improve counterfeit currency detection by analyzing security features present in currency notes. Improving the model's robustness under extreme conditions such as low lighting, severe folds, or damaged notes can further enhance the practical usability of the system.

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