

Currency Denomination Recognition using Deep Learning: A Comprehensive Study on Indian Currency with Convolutional Neural Networks

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Abstract—Tangible currency is an integral aspect of daily lives, and discerning its denomination can pose a considerable challenge. In the digital age, the field of computing unfolds vast possibilities for groundbreaking achievements. The exploration of object detection from images has emerged as a captivating research avenue in recent years, leveraging various deep learning techniques. As part of the training and testing datasets, this framework is designed to recognize and identify currency denominations based on trained images of Indian currency in seven different orientations. Employing a Convolutional Neural Networks (CNN), model ensures the precise extraction of features, as evidenced by experimental results showcasing a commendable 98.32% training accuracy and 83.48% validation accuracy.

Index Terms— Deep Learning, CNN, Max Pooling, ReLU.

I. INTRODUCTION

Object identification in images and neural network training through Deep Learning (DL) have become increasingly popular due to the increasing focus on innovative advances in artificial intelligence. A subset of machine learning, DL uses algorithms to analyze information, mimicking the human brain. Information is processed, objects are recognized, and human voices are comprehended utilizing layers of algorithms, each layer receiving data from the previous layer to be processed. The data processing is further enhanced by the inclusion of hidden layers. In modern computer vision systems, CNN serves as a foundational element of DL. By thinking of images as arrays of pixels, CNN facilitates pattern recognition by identifying simple and complex cells in an image. In today's digital era, the seamless integration of technology into various aspects of human life has become increasingly prevalent. Among the myriad of technological advancements, the development of DL frameworks, particularly CNNs, has revolutionized the field of image recognition and object detection[14].

Using CNNs, which are inspired by the structure of animal vision, able to recognize faces, detect objects, analyze medical imagery, and evaluate medical images. One crucial application of CNNs lies in the domain of currency denomination identification, a task that holds significant practical importance in daily transactions, financial systems, and Automated Teller Machines(ATMs). With the advent of digital payment systems and the ubiquity of electronic transactions, accurately identifying currency denominations has become a pressing need in

modern society. Moreover, for visually impaired individuals, reliable currency denomination recognition systems can significantly enhance their independence and financial autonomy.

In the context of Indian currency, which encompasses a diverse range of denominations and intricate design elements, the accurate identification of currency notes presents unique challenges. The varying sizes, colors, and orientations of Indian banknotes further compound the complexity of the recognition task. Manual identification of currency notes, particularly in large-scale transactions or in environments with limited visibility, can be error-prone and time-consuming. Thus, there is a compelling need for automated systems capable of swiftly and accurately identifying Indian currency denominations. This research endeavors to address this need by proposing a robust framework for Indian currency denomination identification leveraging CNNs. By harnessing the power of DL techniques, this framework aims to enable efficient and reliable recognition of Indian currency notes across diverse scenarios and conditions. The utilization of CNNs facilitates the extraction of discriminative features from currency images, enabling the system to distinguish between different denominations with high accuracy and precision. Furthermore, this research explores the practical implications and societal impact of deploying automated currency denomination recognition systems in real-world settings. Beyond enhancing the efficiency of financial transactions and banking operations, such systems have the potential to foster financial inclusivity and accessibility for individuals with visual impairments or disabilities.

This study aims to demonstrate the effectiveness and reliability of CNN-based currency denomination identification through rigorous experimentation and evaluation. By achieving high levels of accuracy and robustness, this framework aims to pave the way for the widespread adoption of automated currency recognition technologies, thereby enhancing the efficiency, accessibility, and inclusivity of financial systems in India and beyond.

II. LITERATURE REVIEW

The recognition and identification of currency denominations have gained considerable attention recently due to their significance in various automated systems and financial applications. For accurate and efficient identification of currency denominations, DL techniques, like CNNs[11], have emerged as a promising approach. CNNs have demonstrated remarkable capabilities in identifying a range of currency denominations by extracting discriminative features from images, enabling robust classification. Researchers have extensively explored the application of CNNs in currency denomination identification, focusing specifically on various national currencies, including the Indian rupee.

In a study by [1], the authors proposed a method that utilizes currency features such as the center numeral, latent image, RBI seal, shape, and micro letter for currency recognition. The preparation of the training dataset for acquiring training models is elucidated, along with PCA analysis for paper currency recognition.

In another work by [2], authors presented a method that employs features such as color, texture, and size for paper currency recognition, including a method for recognizing dirty banknotes.

Moreover, [3] introduced a system for paper currency recognition using the MATLAB tool, explaining PCA analysis along with Euclidean Distance and employing the LBP technique for matching purposes.

Additionally, [4] discussed CNNs, detailing different layer processing through mathematical demonstrations. The process involves converting the captured image into matrix format before detection, followed by matching with a trained model. The effects of different convolutional kernels on horizontal and vertical edges are also explored.

Using machine learning and DL techniques, N.A. J. Sufri et al. [8] developed an automated vision recognition and classification program for Malaysian Ringgit banknotes. In comparison with k-Nearest Neighbors (kNN) and Decision Tree Classifier (DTC), Support Vector Machine (SVM) and Boosting Classifier (BC) performed more consistently. However, during testing on a new database with different orientations, AlexNet showed sub optimal performance. Similarly, Faiz M. Hasanuzzaman et al. [9] utilized Speeded-Up Robust Features (SURF) and devised a novel component-based banknote recognition system to address various challenging scenarios encountered in real-world environments, achieving high recognition accuracy. A significant challenge faced by the visually impaired is dealing with money. Normally, a normal individual can identify any banknote easily, but the visually impaired have difficulty. In this paper, different CNN models are used to classify Indian currency into seven classes, and the most accurate model is predicted for the data. Identifying features or classifying images does not require all pixels.

In conclusion, the literature survey highlights the growing interest and advancements in the application of CNNs for Indian currency denomination identification. By leveraging DL techniques and innovative model

architectures, researchers continue to enhance the accuracy and efficiency of automated currency recognition systems, enabling diverse real-world applications in banking, retail, and ATMs.

III. METHODOLOGY

An operational flowchart as shown in Fig.1 for Indian currency identification would outline the sequential steps involved in the process, from capturing an image[13] of the currency to determining its denomination using DL techniques. Here's an explanation of the operational flowchart. The process begins with capturing an image of the Indian currency using a camera or any other imaging device. This image serves as the input to the currency identification system. Then acquired image undergoes preprocessing steps to enhance its quality and make it suitable for analysis. Preprocessing may include operations such as resizing, normalization, noise reduction, and color correction. In Feature Extraction stage relevant features of the currency image are extracted to facilitate denomination identification. Features may include elements such as the currency's numerical value, symbols, patterns, and other distinctive characteristics.

The preprocessed image with extracted features is passed through a DL model, particularly a CNN, which has been trained to recognize and classify[12] Indian currency denominations. The CNN analyzes the input image and identifies patterns and features indicative of specific denominations. Denomination Classification based on the analysis performed by the DL model, the system assigns a denomination label to the currency image. The denomination classification process involves comparing the extracted features with the patterns learned during the model training phase.

The proposed explanation is reasonably straight forward classifying Indian currency notes using DL develop approaches. It contains images of approximately seven denominations of Indian currency in all orientations, and consists of 2566 images for training and 436 images for testing. Preprocessing represents the images are standardized and augmented. After this preprocessing, the images are divided into training and testing images. First the model is trained through CNN algorithm. It extracts deep features from the currency note. The image is distributed through a stack of convolutional layers and the filters are used. In this there is fully connected layer followed by an output soft-max layer.

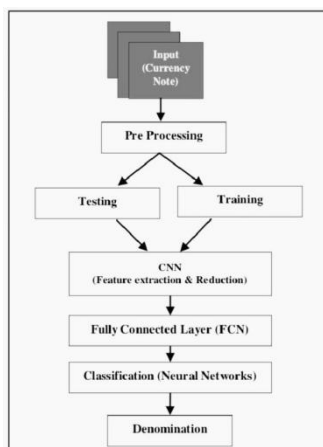


Fig 1: Operational Flowchart

IV. PROPOSED MODEL

In the DL CNN model, each image is trained and tested by convolutional layers, pooling, filtering, connecting layers, and activation functions between 0 and 1. As input image passes through these layers, features are extracted using convolutional layers. It consists of four layers: Convolutional, Max Pooling, ReLU, and Fully Connected. In this system, the input image is divided into RGB channels of size 150x150x3, using a 3x3 filter size, and a stride of 1, resulting in dimensions of 32x32x16 after the first convolutional layer. The subsequent layers include max pooling to reduce image size and error rates, and the fully connected layer employs a vector from the flatten layer with 512 units, forwarded to Softmax for classification into one of eight classes.

Some individuals face challenges in identifying currency denominations due to visual disabilities, image complexion, or lighting conditions. This paper leverages the CNN model of DL to address this issue. Input images of various denominations are presented to the system in order to train them against previously trained

data and display the corresponding denomination for each input image, which is then used to train a model file containing weights passed to neural connections in the convolutional layer. Image features are compared with reference images, and if the difference is below a threshold, the numeric part of the currency is extracted. Recognition occurs if it matches predefined denominations such as 50, 100, 500, 2000, 20, and 10 through image processing and various DL algorithms, with the CNN model ensuring accurate feature extraction.

Implementation Phases:

1. Data Acquisition/Data Collection: Data collection serves as the fundamental module and the initial step in the project. This phase primarily involves gathering the appropriate dataset.
2. Data Preprocessing: Data preprocessing encompasses the transformation of raw data into a more cohesive format. Raw data is often inconsistent or incomplete, containing numerous errors that need correction.
3. Encoding Data: This step involves converting categorical text data into a numerical format understandable by the model, utilizing encoding techniques.
4. Prepare Data / Split Data: The train-test split procedure is employed to assess the performance of machine learning algorithms. This involves dividing the dataset into two subsets:
5. Train Dataset: Utilized to fit the machine learning model.
6. Test Dataset: Employed to evaluate the fitted machine learning model.
7. Training Model: Training the machine involves feeding data to the algorithm to refine its performance on the test data. Training sets are utilized to tune and fit the models, while the test sets remain untouched, as a model should not be judged based on unseen data.
8. Testing Model: The test sets remain untouched during this phase, as models should not be evaluated based on unseen data. Testing model performance involves assessing the models with new data sets and comparing their performance metrics, such as accuracy and recall, against predetermined benchmarks for the model.

V. SYSTEM ARCHITECTURE

CNN undergoes a series of layer for processing the data to achieve better accuracy with low dimensional features. The model is designed for the recognition and classification of Indian currency notes based on their denominations. The model as shown in Fig. 2 follows a structured architecture with distinct stages:

Input Stage (Indian Currency Note): The input to the model is an image of an Indian currency note. This image serves as the raw data that the model will analyze and classify.

CNN Feature Extractor: CNNs are employed as the feature extractor. This stage involves multiple convolutional layers, each responsible for detecting and learning different features from the input image. Convolutional operations capture spatial hierarchies of features, recognizing patterns such as edges, textures, and shapes relevant to currency denomination identification. Pooling layers down-sample the spatial dimensions, reducing computational complexity while retaining essential features.

Fully Connected Layer: Following the feature extraction, a fully connected layer is introduced. This layer connects every neuron from the previous layer to each neuron in the subsequent layer. The purpose is to combine the high-level features extracted by the CNN into a comprehensive representation that can be used for classification. This stage allows the model to understand complex relationships between different features and their relevance to currency denomination.

Softmax Layer: The final stage of the model is the softmax layer. It serves as the output layer responsible for generating probability distributions over different currency denominations. The softmax function converts the raw output scores from the previous layer into probabilities, indicating the likelihood of the input belonging to each denomination class. The model predicts the denomination with the highest probability as the final classification.

The visual representation in Fig. 3 illustrates the systematic flow of information across various layers, elucidating the intricate processes of feature extraction, dimension reduction, and classification within the CNN. This network's primary goal is to derive meaningful features from input images, facilitating accurate identification and classification.

The essential components of the architecture include:

Convolutional Layer: This layer identifies features in an input image through mathematical computations with a pixel matrix and a filter (or kernel). In this case, a 3x3 kernel is utilized with a 48x48 matrix, representing the input image's size.

Pixel matrix: $h \times w \times d$

Filter: $(f_h \times f_w \times d)$

Mathematical operation: $(h-fh-1) \times (w-fw+1) \times 1$

Padding: Padding is employed to add extra pixels to the image, compensating for the reduction in size caused by the application of filters or kernels.

Pooling Layer: This layer minimizes image dimensions by consolidating results from a set of neurons in one layer to a single neuron in the next layer.

ReLU Layer: ReLU, or Rectified Linear Unit, serves as an activation function, determining the vitality of neurons with the function

$$y = \max(0, x).$$

Fully Connected Layer: This layer establishes connections between neurons across layers. The matrix from the ReLU layer is flattened into a vector and forwarded to neurons in the subsequent layer.

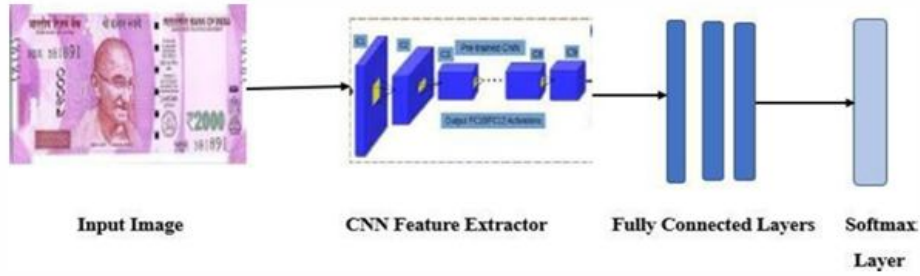


Fig. 2: Overall CNN Architecture of the Model

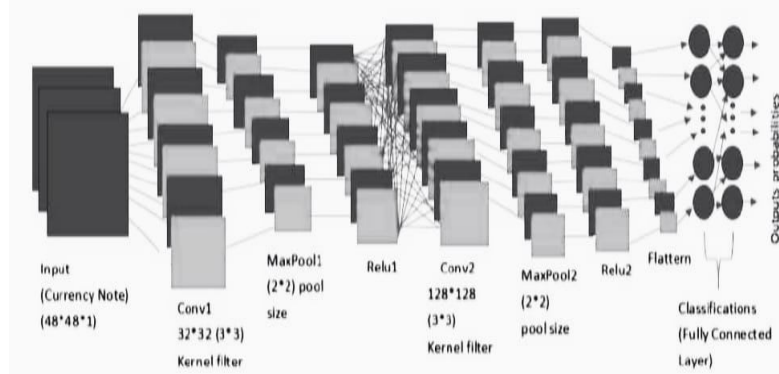


Fig 3: Systematic flow of information between different CNN Layers

The system processes a set of images representing various currency denominations as input. In the initial iteration, the system analyzes the image for identification, converting a portion of the image into a matrix format. Filters, along with weights, are then applied to this matrix.

The creation of a prototype system capable of recognizing the denomination of Indian currency notes represents a significant advancement. Employing the gTTS (Google Text-to-Speech) Python library and API, the system excels in converting text into spoken words, enabling it to produce audio messages announcing the denomination of a banknote. This innovative solution processes images, delivering audio messages through either earphones or speakers. The potential impact of this groundbreaking development extends to aiding the visually impaired, providing an accessible and informative tool for currency recognition.

VI. RESULTS AND DISCUSSIONS

This endeavor is executed through the utilization of open-source software, specifically Python, formulated within the Keras library with TensorFlow serving as the underlying framework. The dataset is systematically generated to cater to both testing and training requirements, subsequently imported into the system, and subjected to processing by means of a Convolutional Neural Network (CNN) model. This model, in turn, generates a file encapsulating its weights. Upon introduction of input data to the system, a resizing operation is executed through pre-processing techniques, concomitant with the extraction of salient features from the images. Subsequent to this prelude, the model undergoes training against the designated training data. This involves convolutional processes over 25 epochs, employing a batch size of 100 for classification purposes, culminating in the identification and display of recognized denominations. Noteworthy in this methodology is the application of dual convolutions for each denomination during every epoch.

The proffered approach has yielded a commendable accuracy rate of 98.32% on the training dataset and 83.48% on the validation dataset. The imperative need for automated currency processing systems has arisen due to multifarious applications. However, the inherent complexity stems from the distinctive features and security nuances inherent in various currencies. Numerous methodologies have been posited for the identification of currency denominations, encompassing the juxtaposition of image features against reference images. If the variance falls below a predetermined threshold, the numerical component of the currency is extracted, and subsequent matching results in the recognition of the denomination.

To uphold the pinnacle of accuracy in denomination identification, it is imperative that the dataset undergoes training with minimal data loss. This necessitates the inclusion of a substantial number of values in the dataset for training purposes, thereby amplifying the accuracy percentage. For visualizing pertinent metrics, such as loss and accuracy statistics during the neural network's training phase, graphical representations are plotted for meticulous tracking and analytical endeavors. Figures 4 and 5 delineate the accuracy and loss percentages accrued throughout the dataset's training, accompanied by their corresponding values across epochs. The dimensions of these plotted graphs elucidate the fluctuations in weight values as the number of images undergoes training for a specified duration of epochs or time.

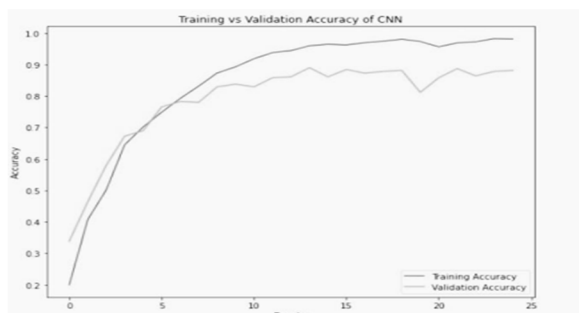


Fig 4: Disparity Between Training and Validation Accuracy of CNN.

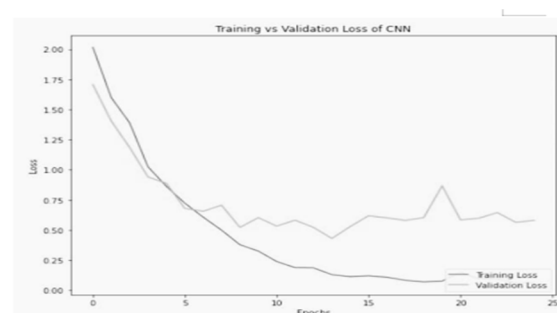


Fig 5: Disparity Between Training and Validation Loss of CNN

A CNN model is found to be effective at identifying a currency denomination in a dataset in this study, as evidenced by the study's conclusion. The model uses innovations related to robustness and computation to recognize Indian currency denominations, resulting in high accuracy for the dataset, which contains Indian currency denominations of 10, 20, 50, 100, 200, 500, and 2000.



Fig. 6: Currency prediction in Indian notes along with voice messages

Accurate classification of Indian currency is essential for secure financial transactions, and employing DL techniques, such as CNN models, proves to be an effective solution. Fig. 6 displays the output results, demonstrating the proper and precise identification of each currency note along with an accompanying voice message.

V. CONCLUSIONS

This study emphasizes the importance of utilizing CNN models for identifying currency denominations, especially in the context of the Indian currency dataset comprising denominations like 10, 20, 50, 100, 200, 500, and 2000. It explores innovative approaches to enhance the accuracy and efficiency of recognizing Indian

currency denominations within a computational framework. The necessity of physical currency in daily transactions, along with the challenges of manual identification, underscores the significance of automated solutions. In today's digital age, leveraging machine capabilities is crucial. The proposed framework employs various DL techniques, with a focus on the CNN model for accurate feature extraction. By addressing the complexities of currency denomination identification, this research contributes to object detection in images. The comprehensive dataset, with seven Indian currency denominations in different orientations, forms a strong basis for experimentation. The CNN model demonstrates impressive results, achieving 98.32% training accuracy and 83.48% validation accuracy. This work not only showcases CNN models' effectiveness in currency denomination recognition but also offers insights into broader image-based object detection. The methodologies and algorithms explored pave the way for automating currency-related tasks, advancing computer vision applications. Future research could focus on refining the model for adaptability to various currency types, expanding its applications in automated currency recognition.

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