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A Review on Currency Classification and Image to Text Conversion Methodologies

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Abstract:- Currency classification and Image to Text OCR are essential technologies that find applications in various domains, including finance, retail, and automation. The approach outlined in this paper has the potential to detect currencies from multiple countries. However, for practical implementation purposes, the focus is solely on Indian paper currencies. This system offers the advantage of convenient currency checking at any time and location, leveraging Convolutional Neural Networks (CNN) for effective implementation. Extensive testing was conducted on each denomination of Indian currency, resulting in an impressive 95% accuracy rate. To further refine accuracy, a classification model was developed, incorporating all pertinent factors discussed in the paper. Notably, the unique features of paper currency play a pivotal role in the recognition process. By emphasizing these elements and harnessing CNN technology, the proposed system demonstrates significant promise in accurately detecting and validating Indian paper currencies. It stands poised to serve various applications effectively. On the other hand, Image to Text OCR focuses on extracting text from images, enabling the conversion of non- editable documents into searchable and editable formats.

Both technologies contribute to automation and efficiency in handling diverse visual information. Optical Character Recognition (OCR) is a technologydesigned to recognize and interpret both printed and handwritten characters by scanning text images. This process involves segmenting the text image into regions, isolating individual lines, and identifying each character along with its spacing. After isolating individual characters from the text image, the system conducts an analysis of their texture and topological attributes. This involves examining corner points, unique characteristics of various regions within the characters, and calculating the ratio of character area to convex area Prior to initiating recognition, the system creates templates that store the distinctive features of uppercase and lowercase letters, digits, and symbols.

These templates serve as reference models for comparison during the recognition phase. During recognition, the system matches the extracted character's texture and topological Features with those stored in the templates to determine the exact character. This matching process involves comparing features of the extracted character with templates of all characters, measuring similarity, and ultimately recognizing the character accurately.

***Keywords**:- Currency Recognition, CNN, OCR, Deep Learning.*

I. INTRODUCTION

The World Health Organization (WHO) reports that globally, an estimated 285 million people are visually impaired, with the majority residing in developing nations. Among them, approximately 45 million individuals are blind. Despite available solutions, none fully replicate the reading experience of sighted individuals, highlighting the need for an affordable, portable text reader for the visually impaired.

A proposed solution involves creating a smart device with a multimodal system capable of converting any document into an accessible format. This device would enable blind individualsto read through tactile feedback and auditory output via a text-to-speech engine, providing an experience akin to sighted individuals.

Visually impaired individuals encounter challenges in daily tasks, including identifying items or information, leading to difficulties in navigating new environments. This is especially problematic in scenarios like correctly identifying medications. Thus, innovative solutions such as smart devices and mobile applications are essential to enhance accessibility and quality of life. Technology, particularly mobile phones, plays a pivotal role in facilitating communicationand access to information for the visually impaired. Technologies like text-to-speech conversion and optical character recognition (OCR) enable effective interaction with computers through vocal interfaces.

In conclusion, addressing challenges faced by visually impaired individuals in accessing information and navigating their environment is crucial. Innovative technological solutions can significantly improve accessibility and inclusion for this community.

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II. BACKGROUND AND RELATED WORK

The idea we're presenting isn't entirely original, especially regarding the recognition of Indian currency. Previous attempts have been made to tackle this challenge. However, our approach seeks to streamline the currency recognition process, making it more efficient and less resource- intensive. We aim to develop a solution that can operate effectively on lower-end computing devices. In this section, we will review past efforts in this field, identifying their shortcomings and outlining areas where improvements can be made.

➢ *Traditional Method*

- *The Scanning Module's Layout:*

The primary function of the sensing unit is to collect data from the input bill and forward it to a processing module. There are six emitter-sensor pairs in all. Where each infrared (IR) emitter is matched with a photosensor. These pairs are integrated within the device, positioned opposite each other on both sides of a bill that was inserted. To provide accurate and consistentreadings, the emitters face upward and the photosensors are positioned downward toward the banknote.

To provide accurate and consistent readings, the emitters face upward and the photosensors are positioned downward toward the banknote. Different Indian rupee denominations exhibit distinct patterns when viewed with infrared vision due to varying amounts of infrared light in different areas. To accommodate the size differences of Indian rupees, sensors are strategically placed at the beginning and end lengths of the note for accurate detection.

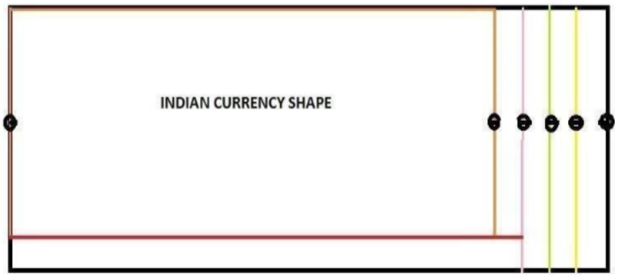

Fig 1:- The layout for sensor placement is illustrated

In the scanning module, different colors signify various denominations, and the circle inside each color denotes the placement of the sensor. The size of Indian currency notes are specified in Table1 and the scanning module's sensors comply with these requirements. The start of each note is indicated by the black barrier on the left. The dimensions of a 1000 rupee note are represented by the outside black boundary, while the dimensions of 500, 100, 50, 20, and 10 rupee notes are represented by the colors yellow, green, pink, red, and orange, respectively.

Table 1. Dimensions and Color of Different Denominations

Numbering(in Rupees)	Length in millimeters	Width in millimeters	Shade	Forms
10	137	63	Orange Violet	Not specified
20	147	63	Red Orange	Not specified
50	147	73	Violet	Not specified
100	157	73	Bluish Green	Not specified
500	167	73	Olive and Yellow	Not specified
1000	177	73	Pink	Not specified

- Pros: Provides tactile differentiation for various denominations, Simple and intuitive for blind individuals to use, doesn't require additional equipment or technology, universally applicable to all blind individuals.
- Cons: Limited to physical currency only, doesn't provide additional information like condition or authenticity.

A. Feature Extraction

Six unique characteristics are taken from each currency note in the manner outlined for identifying paper money in Indian rupees. Two of these attributes are especially used to determine the currency's denomination, which helps the system choose the right currency template.

The next step for the system is to determine how similar each feature is to the matching feature template linked to a certain denomination after it has been retrieved from the input currency image. Higher similarity traits receive a vote of one, whereas lower similarity features receive a vote of zero. The system then counts the number of features that got a single vote. If the count of features receiving a vote of one exceeds a certain threshold, the currency is classified as known; otherwise, it is classified as unknown. The features extracted from the currency note are represented in Figure 2, while the architecture of the proposed method is illustrated in Figure 3. This approach aims to effectively classify Indian rupee currency notes by leveraging specific features and similarity calculations

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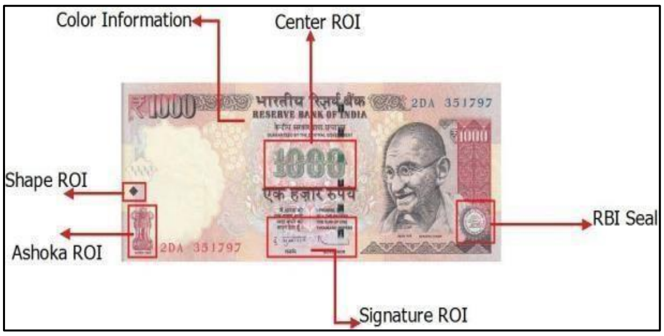

Fig 2: Interest Region at the Currency Images Fixed Position

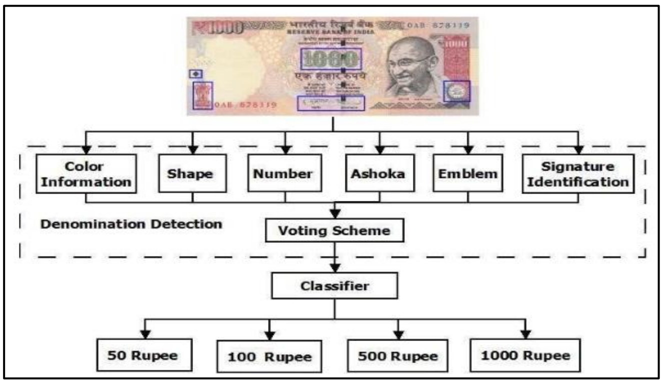

Fig 3: The Paper Currency Recognition System's Architecture

- Pros: Accessibility for blind individuals, Reliability and consistency, Cost-effective, Universal design, Privacy preservation
- Cons: Learning curve, Limited information provided, Subject to wear and tear, Limited functionality, Dependence on physical currency

Table 2. Table of Comparison:

Author/s	Dataset Used	Techniques/Methods- Used	PerformanceMeasures
[1] Zhang & Yan(2018).	Due to the lack of dataset,Self-generated data used.	6-layer CNN Model	Testing Accuracy:90%
[2] Kamble et al. (2019)	Because of the absence of informational collection, self-creating it was obligatory.10, 000 picturesof every class were produced. In this way, there were a sum of 40,000 pictures	The proposed approach forfinding of fake note is grounded on CNN design.	Accuracy of Testing:85.6%. Accuracy of Preparing: 98.57%. Accuracy of Approval:96.55%. Precision is: 85.8% Review: 86.00%
[3] Pokala & Teja(2020)	Data Collection for development of, the imageProcessing code.	Image processing code usingBrute Force Matcher algorithm	Testing Accuracy: Poor
[4] Nijil Raj N (2020)	Data-set used is Indiancurrency. The data-set comprises many Indian currencie'sof, Rs20, Rs50, Rs100, Rs200, Rs500.	VGG16 Convolutional Neural Network (ConvNets)	k-N-N and D-T-C Accuracy of Testing:99.7%. 'SVM' and 'BC' Accuracy ofTesting: 100%.
[5] Raghad RaiedMahmood , Dr. Majid DherarYounus (2021)	Self-built Iraqi bank notedataset	YOLOv3 model	Accuracy – 97.405 %

B. Need of Proposed System:

Currency classifications are driven by the urgent needs of our fast-paced, modern society. These technologies are motivated by several important elements that solve pressing issues and seize chances to increase accessibility, accuracy, and efficiency. Automated currency classification eliminates the need for human counting and verification by ensuring quick and error-free transaction processing. This reduces the possibility of errors brought on by human participation while also speeding up financial activity's technology converts scanned documents or photosinto editable, searchable text automatically. For companies that deal with a lot of paperwork, this is revolutionary since it makes data extraction, information retrieval, and document management.

C. Research Gap

- The main aspect or challenge in the currency recognition is accuracy.
- To achieve the accuracy many of system uses different algorithms.
- These system ensure for currency recognition but not the accuracy.
- Currency recognition and currency detection plays an important for these kind of system.

D. Existing System:

Commercial Currency Sorters: Financial institutions and businesses use currency sorting machines that incorporate image processing and pattern recognition

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algorithms. These machines can identify and sort different denominations based on various features, such as size, color, and security features.

- ATMs (Automated Teller Machines): ATMs are equipped with currency recognition capabilities to authenticate and handle banknotes of different denominations. These systems employ a combination of sensors and image processing techniques.

- Retail Automation Systems: Some retail environments use automated systems that can recognize and process various currencies during transactions, providing efficiency and accuracy in cash handling.

- Google Cloud Vision OCR: This OCR feature allows you to extract text from documents and images on Google Cloud. It supports multiple languages, and the extracted text can be used for various applications, such as document analysis and content indexing.

- Tesseract OCR: Google created Tesseract, an open-source OCR engine. It is frequently used to identify text in documents and photos. Tesseract supports multiple languagesand can be customized for specific applications.

- Adobe Acrobat OCR: Adobe Acrobat includes OCR functionality for converting scanned documents into editable and searchable text. It is commonly used for document management anddigitization.

III. PROPOSED SYSTEM

Develop and train an advanced machine learning model for currency classification. Utilize deep learning techniques, such as convolutional neural networks (CNNs), to improve the system's ability to recognize various currencies, including different denominations and security features. Implement state-of-the-art OCR algorithms, including those based on deep learning architectures, to improve the accuracy of text extraction from images. Consider techniques like attention mechanisms for handling complex document layouts.

➢ *System Architecture Currency Classification:*

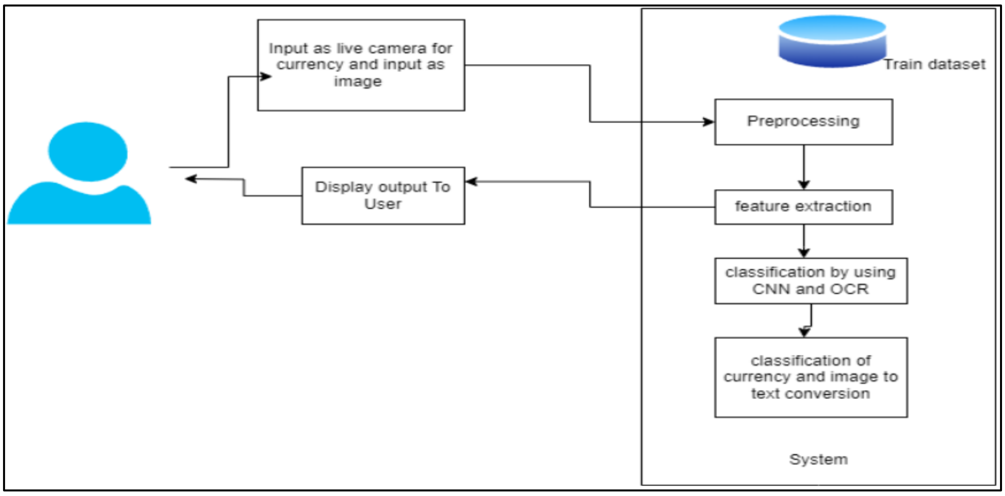

Fig 4: System architecture

- Convolutional Neural Networks Certainly! Here's Convolutional Neural Net- works (CNNs) encode images into vector representations:

- Input Image: CNNs take an image as input.

- Convolutional Layers: They use filters to extract features like edges and shapes. Activation Function: Apply functions to capture complex relationships.

- Pooling Layers: Down-sample to retain key information. Flattening: Convert feature maps into a1D vector.

- Fully Connected Layers: Capture relationships and output a vector.

- Output: The final vector represents the image and is used for tasks like classification and object detection.

- OCR Algorithm: Optical Character Recognition (OCR) is a computer vision process used for detecting and interpreting text within images. It plays a vital role in enabling Natural Language Processing algorithms to comprehend the content of documents.

- Input Layer: This layer consists of grayscale images representing text-containing documents. Output Layer: The identified text or characters are indicated by binary or multi-class labels produced by the output layer.

- Secret Layers: A fully connected neural network, pooling layers, ReLU (rectified linear unit)layers, and convolutional layers are some examples of these layers.

It's crucial to remember that Artificial Neural Networks (ANNs), which are made up of many neurons, cannot directly extract features from pictures. Convolutional and

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pooling layers are used to address this. Though these layers are quite good at extracting features, they are not appropriate for jobs involving categorization. For categorization, a fully linked neural network is therefore required. Understanding each section independently is crucial before delving further into these ideas.

IV. CONCLUSION

In summary, the investigation of the categorization of cash demonstrates their significant influence on a number of facets. These innovations in machine learning and image processing are revolutionizing the way we engage with visual data, streamlining workflows, and improving accessibility. By automating the identification and management of various currencies, currency classification simplifies cross-border trade, retail operations, and financial transactions technology increases productivity by streamlining document management. Reducing manual labor and mistakes is achieved by data extraction and the transformation of images into editable and searchable text. Systems for classifying currencies are essential to international trade because they facilitate smooth transactions and eliminate obstacles brought on by currency variability. By enabling people with visual impairments to access printed and handwritten information, OCR improves financial inclusion and fosters an inclusive digital environment.

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