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Multi Country Currency Finder Using Oriented Fast and Rotated Brief for Destitute of Vision

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ABSTRACT

This paper presents Multi Country Currency Finder Using Oriented Fast and Rotated Brief for Destitute of Vision, a novel system designed to help individuals with visual impairments recognize the denomination of paper currency. The system uses image processing and deep learning techniques to recognize the denomination of paper currency notes, and it is designed to be user-friendly, accurate, and accessible to all individuals with visual impairments. Multi Country Currency Finder Using Fast and Rotated brief for Destitute of Vision is an end- to-end solution that covers the entire process of currency recognition, from image acquisition to output. The system includes a camera that captures images of the currency notes and a software program that processes the images to recognize the denomination. The output of the system is highly accurate, ensuring that individuals with visual impairments can confidently manage their finances. The system can recognize all denominations of paper currency, making it useful for individuals across the globe. In addition, Multi Country Currency Finder Using Fast and Rotated brief for Destitute of Vision is cost-effective and easy to use, making it a valuable tool for individuals with visual impairments in listed currencies (India, America). Overall, Multi Country Currency Finder Using Fast and Rotated brief for Destitute of Vision represents an important innovation that can improve the daily lives of individuals with visual impairments, providing them with an effective and accessible solution for currency recognition.

Keywords — multi-currency banknote recognition, visual impairments, image processing, deep learning, accessibility;

I.INTRODUCTION

Multi Country Currency Finder is a multi-currency banknote recognition system designed to assist individuals with visual impairments in identifying the denomination of paper currency notes. The system employs image processing and deep learning techniques to recognize the currency denomination, and it is specifically designed to be user-friendly, accurate, and accessible for all individuals with visual impairments. Mulit Country Currency Finder Using Fast and Rotated brief for Destitute of Vision provides an end-to-end solution that covers the entire process of currency recognition, from image acquisition to output. The system includes a camera that captures images of the currency notes and a software program that processes the images to recognize the denomination. The output of the system is delivered through a voice-based interface, enabling users to hear the denomination of the currency. The system is highly accurate in recognizing all denominations of paper currency notes, making it a useful tool for individuals across the globe. The system is cost-effective and easy to use, making it an important innovation that can improve the daily lives of individuals with visual impairments in the listed currencies (India, America). Overall, Multi Country Currency Finder Using Fast and Rotated brief for Destitute of Vision is a significant advancement in currency recognition technology for individuals with visual impairments. Its user-friendly interface, high accuracy, and cost-effectiveness make it a valuable tool that can help these individuals manage their finances with confidence.

II.EXISTING SYSTEM

The majority of existing literature on currency recognition systems is limited to theoretical or desktop/web-based systems. There are few commercial and non-commercial currency recognition systems available for mobile devices, such as Look Tel Money Reader2 and IDEAL Currency Identifier, but they have limited performance for folded or wrinkled currencies and do not support Indian currencies. Microsoft's Seeing AI app supports Indian currencies but performs poorly when the currency is folded and does not provide correct results for some new currency denominations, like the new INR 100. To meet the needs of blind and visually impaired people, the Reserve Bank of India launched the MANI app for android. However, there is no publicly available information or resources regarding the prediction models/methods used in these apps. The core features of these apps vary, and the majority of previous work uses smaller datasets. Additionally, very few studies have used multiple datasets for evaluation, which is critical for validating the generalization ability of underlying models. The compatibility with BVIP and the availability of related real-time applications are major concerns in the existing literature and the most commonly used models are.

1) Depth wise separable convolution

The proposed network in this work uses depth wise separable convolutions, which consist of depth wise and pointwise convolutions. The depth wise convolution applies individual filters to each input channel, followed by the pointwise convolution to combine the output. This reduces the model computations and size, and the 3x3 depth wise separable convolutions reduce the computation by 8 to 9 times. The depth wise convolution is performed using a single filter perinput channel, while the pointwise convolution uses 1x1 filters. The total cost associated with the conventional convolution operation involves the number of input and output channels, kernel size, and feature map size. This cost can be reduced using depthwise separable convolution, where the collective filtering and combination steps of the conventional convolution operation are split into two steps. The ratio of the number of computations in depthwise separable convolution and that of the conventional convolution process is given as [1/Q x 1/D^2 K], which shows the reduction in computations from the conventional convolution scheme to depthwise separable convolution

2) Dilated depth wise separable convolution

The proposed contextual module employs dilated depth wise separable convolutions, which expand the receptive field without adding extra model complexity or channels. In the dilation process, each filter is dilated

to extract more information. For example, a 3x3 filter with dilation D=2 has a receptive field equivalent to a 5x5 kernel but with fewer parameters. The dilation factor D increases the receptive field without adding extra parameters. The enlarged receptive field helps to extract finer semantic details, which improves the overall accuracy of the model. The stacking of these dilated layers further enlarges the receptive field, as shown in equation. Standard dilation schemes using the same or increasing dilation factors across layers fail to capture local features and contextual information, leading to aliasing in higher layers. By contrast, the proposed dilated depth wise separable convolutions capture both local features and contextual information, making the model more accurate. The dilation operation is represented by equation (4) and is a
2-D operation involving input and output. The kernel k(i,j)
has height R, width S, and dilation factor d. The enlarged receptive field (Z) of a dilated convolution layer with a filter size of k x k is given by equation.

III.LITERATURE SURVEY

The field of computer vision and image processing has seen significant progress in recent years, thanks to the advancements in deep learning and machine learning algorithms. The use of these techniques has led to the development of numerous applications that cater to the needs of various domains. In the context of image classification, Sehla Loussaief and Afef Abdelkrim proposed a machine learning framework in 2016 that utilized convolutional neural networks (CNNs) for improved classification accuracy. Similarly, Jia Deng et al. introduced a large-scale hierarchical image database in 2014 that provided a benchmark for evaluating object recognition algorithms. In 2017, Andrew G. Howard et al. presented efficient convolutional neural networks that were designed for mobile vision applications, with a focus on reducing the computational complexity of the networks. In 2019, Jie Hu et al. proposed squeeze-and- excitation networks that utilized attention mechanisms to enhance the representational power of CNNs.

The use of deep learning techniques has also led to the development of various applications that cater to the needs of visually impaired people. Jay Jhaveri et al. proposed an independent aid for the visually impaired in 2018, which utilized computer vision techniques to assist the visually impaired in navigating their surroundings. In the same year, Reserve Bank of India developed a mobile application that identified the denomination of Indian banknotes to aid visually impaired individuals. Additionally, Chanhum Park et al. proposed a deep feature-based three-stage detection system for banknotes and coins in 2020, which aimed to assist visually impaired people in identifying money.

Disadvantages

- Limited detection range
- May not work well with damaged or torn banknotes

While these advancements have significantly improved the accuracy and efficiency of computer vision and image processing techniques, there are still challenges that need to be addressed. One of the major challenges is the limited interpretability of deep learning models, which makes it difficult to understand how the models arrive at their decisions. Another challenge is the need for large amounts of annotated data for training deep learning models, which can be time-consuming and expensive to obtain

Disadvantages

- May suffer from overfitting if not properly regularized

Nonetheless, the continued development and refinement of deep learning techniques have the potential to address these challenges and enable the development of more accurate and efficient computer vision applications in the future.

Disadvantages

- May not have sufficient diversity to represent all real-world scenarios
- May not perform as well with smaller datasets.

IV. PROPOSED SYSTEM

The recognition of currency is of utmost importance for individuals who are blind or visually impaired (BVIP) to actively participate in economic activities and carry out transactions. In order to tackle this challenge, our research proposes the development of a currency detection model that can accurately identify genuine banknotes.

To initiate the process, we collected a comprehensive dataset comprising high-quality currency images, sourced either from reputable online repositories or captured through photographs. To prepare the dataset for model training, several preprocessing techniques were applied, including resizing the images, adjusting brightness and contrast levels, and converting them to grayscale. These steps were crucial in optimizing the dataset and ensuring its compatibility with the subsequent model development stages.

One significant consideration during the development process was the need to create a compact model without compromising its performance. To address this, we employed the compressed TFlite model technique, which involved utilizing various compression methods such as pruning, quantization, and weight sharing. This technique proved invaluable in reducing the model's size, thereby enabling its effective deployment on resource-constrained platforms like mobile devices and embedded systems.

Moreover, our currency detection system encompasses the recognition of banknotes from five different countries. To accomplish this, we integrated the widely-used ORB algorithm into the TF Lite framework. This combination contributed to improved accuracy and efficiency in the currency recognition process.

In conclusion, our research endeavors to enhance the accessibility and independence of BVIP individuals by developing a currency recognition model. Through careful data collection, preprocessing, and model optimization, we have successfully created a compact and efficient system capable of accurately identifying genuine banknotes from multiple countries.

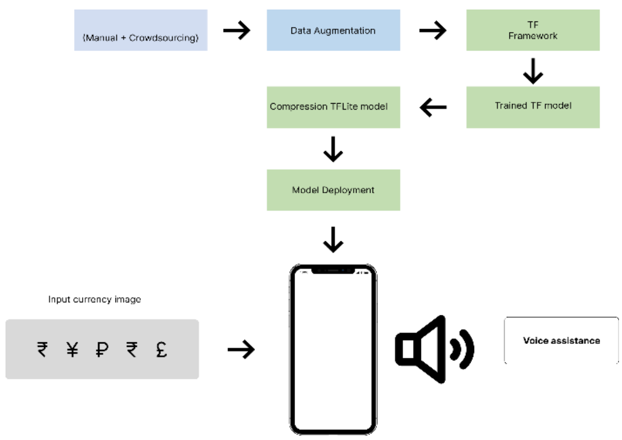

Figure 1. Proposed System Overflow Architecture

1) Developing a Model for Currency Detection Using Deep Learning and Optical Character Recognition

Collecting Data: To create a model that can detect fake currency, you need to collect data about both genuine and fake currency. You can gather images of both types of currency from online sources, or you can take photos of them yourself. The images should be high quality and contain various denominations.

Data Augmentation: The collected data needs to be preprocessed to prepare it for the model.
This can involve resizing the images, adjusting their brightness and contrast, and converting them to grayscale

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Deep Learning Framework: Next, you can develop a model that can classify images as either genuine or fake. There are different approaches you can take, such as using a pre- trained neural network, training your own neural network, or using machine learning algorithms like SVM (Support Vector Machine) or Random Forest.

Trained TF model: A trained TensorFlow model Oriented FAST and Rotated BRIEF (ORB) Algorithm can be used for Optical Character Recognition (OCR) tasks, such as recognizing text in images.

Compression TF Model: Compressed TensorFlow (TF) model is a technique used in deep learning to reduce the size of a model without sacrificing its performance. It involves compressing the model using various methods like pruning, quantization, and weight sharing. This technique is useful in situations where the size of the model is a limiting factor, such as when deploying it on mobile devices or in embedded systems.

Model Deployment: Deploy the final version of the application to a production environment, such as an app store or website, to make it accessible to users. Monitor usage and feedback to identify any issues and continue to improve the application over time.

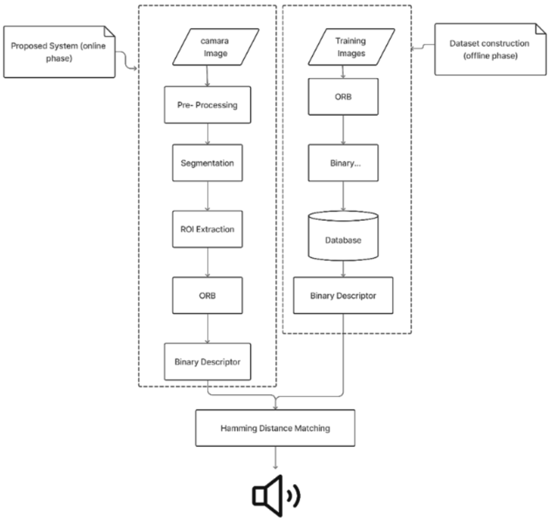

Figure 2. System Architecture

the process is which happen in the model is Preprocessing Some image processing operations are performed to prepare the currency image for segmentation process. Gaussian blurring equation is used to remove noise from the image and then sharpening the image help to segment the currency for the next step.

The Gaussian blurring equation is:

G (x, y) = (1/2πσ^2) * e^(-(x^2+y^2)/2σ^2)

where x and y are the distances from the origin in the horizontal and vertical axes, respectively, and σ is the standard deviation of the Gaussian distribution. The value of σ determines the degree of blurring applied to the image, with larger values resulting in more smoothing. The Gaussian blur is a commonly used. Technique in image processing for removing noise and reducing image details, while preserving the overall structure of the image Segmentation The segmentation process is an essential step in currency recognition, where the main goal is to separate the foreground currency from the background. This separation is achieved by converting the input currency image into a binary image consisting of two colors, black and white. The Otsu Thresholding function is a widely used technique to convert a grayscale image into a binary image. It works by determining an optimal threshold value that can effectively

separate the foreground from the background. In the context of currency recognition, the Otsu Thresholding function is applied to the input RGB image after some preprocessing techniques have been applied to remove noise and enhance the image quality.

The output of this process is a binary image consisting of 0s and 1s, where 0 represents the black background and 1 represents the white foreground. The threshold value th is determined by the Otsu technique, which computes the optimal threshold value based on the image histogram. The image histogram is a graph that shows the frequency distribution of the intensity values of the pixels in the image. The optimal threshold value is the one that maximizes the between-class variance, which measures the separation between the foreground and the background. The binary image obtained from the Otsu Thresholding function is then used to extract the region of interest (ROI), which contains the foreground currency. The ROI extraction process involves detecting the edges of the currency using a contour detection algorithm and then enclosing the edges with a bounding box to define the ROI. Once the ROI is extracted, feature extraction techniques are applied to obtain the relevant information about the currency, such as its size, shape, and texture, which are used to classify the currency denomination.

ROI Extracting In the currency recognition process, the ROI extraction step is crucial to isolate the foreground currency from the background. The two-pass connected component Algorithm is a widely used technique for this purpose. It is a simple and efficient algorithm that can effectively extract the ROI from the binary image generated by the Otsu Thresholding function. the two-pass connected component Algorithm is an effective method for extracting the ROI from the binary image. It is simple and fast and can accurately identify the connected components that belong to the foreground currency.

ORB Feature Extraction In the fourth step of the proposed method, the Oriented Fast and Rotated Brief (ORB) Algorithm is utilized for detecting and describing features of the extracted currency region. The algorithm starts by applying the Fast algorithm to detect corners and interest points in the image. Then, Harris corner detector is utilized to assign a score for each interest point based on the variation of intensities around the corner point. After scoring, the interest points are sorted, and only the top N points are considered.

Next, the intensity-weighted centroid in is computed for the neighborhood of interest points. Finally, the direction vector is calculated and assigned as the orientation of the interest point using the centroid and interest point. The ORB algorithm is chosen because it is robust to scale and rotation changes and can efficiently compute feature descriptors.

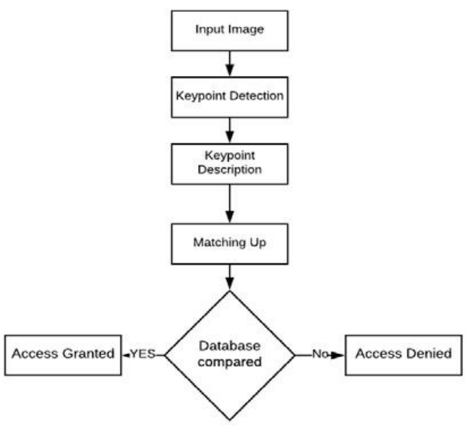

Figure 3. Flow diagram of the ORB algorithm

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ORB Description In the feature extraction stage, the interest points obtained from the previous stage are used to extract feature descriptors using the Brief algorithm. This algorithm creates binary descriptors consisting of 0 and 1 binary numbers, known as local binary descriptors, with respect to a local shape like rectangle or circle. To create these descriptors, the pixel pair sampling method is used where a pair of pixels P1 and P2 is selected from a 31×31 patch around every interest point, and if P1 is greater than P2, a 1 is added to the description vector. The binary descriptors are then computed for each interest point and stored in the database.

This process is performed on the training set to create a database of feature descriptors. The same process is then performed on the currency image captured by the mobile camera to obtain the feature descriptors for matching in the next stage of the algorithm.

τ (P: P1, P2) = {1 $if\ P1 \geq P2$ 0 $otherwise$

This formula represents the test of point 1 (p1) and point 2 (p2), which produces a result of either 1 or 0 depending on the comparison of p1 and p2.

The comparison is done using the pixel pair sampling method, where a pair of pixels P1 and P2 is selected from a
31x31 patch around every interest point, and the intensity values of P1 and P2 are compared. If P1 is greater than or equal to P2, the formula outputs 1; otherwise, it outputs 0. The resulting binary descriptor is made up of a sequence of such tests applied to different pixel pairs.

Matching When a blind user opens the mobile app, they have a few seconds to capture an image of the currency they want to identify. The system then processes this image using the pre-processing steps we previously discussed. The ORB algorithm is then applied to extract binary descriptors from the image.

These descriptors are used to compare the currency image to previously stored images in a database. The Hamming distance measure, shown in equation 4, is used to determine how closely the descriptors match. The Hamming distance measures the number of differences (mismatches) between the descriptors being compared.

If a match is found, the blind user will hear a sound representing the value of the currency they captured. The system can determine the value of the currency based on the matched image in the database. the Hamming distance measure equation for matching binary descriptors is given as:

HAD (i, j) = $\sum (Yi,\ k \neq Yj,\ k)\ n{-}1\ k{=}0$

where D is the Hamming distance between descriptors, i and j are the indices of the respective variables, and k is the index of the binary digit in the descriptor.

The Hamming distance is calculated as the number of bit positions in the binary descriptors where the two descriptors differ.

2) Data set used in this project

Currency recognition is becoming increasingly important in today's global economy, where many different currencies are in circulation.

The dataset was collected in a real-time scenario to incorporate variations in lightning conditions, backgrounds, postures, and angles. While collecting these images, we have included conditions such as folded and full view of

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currency images and the indoor/outdoor environments to capture variability This report outlines a custom dataset and method that uses the Oriented FAST and Rotated BRIEF (ORB) algorithm to accurately Indian (INR), America (USD), Japan (Yen), Saudi (Riyal), United Arab Emirates (Dirham) notes.

Figure 4. Currencies Dataset

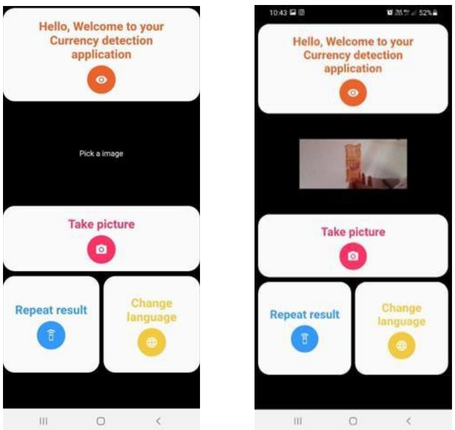

Figure 5. Screenshot of Multi Country Currency Finder app

VI.CONCLUSION

The Multi Country Currency Finder system, a multi-currency banknote recognition system designed for the visually impaired, holds significant importance in improving the daily lives of individuals with visual impairments or blindness. By utilizing this device, individuals can easily differentiate between different denominations of currency, empowering them to carry out transactions and manage their finances independently and confidently.

An ideal currency detector should prioritize user-friendliness and accessibility, incorporating tactile features that allow users to distinguish between various notes through touch alone. Moreover, it should offer reliable and accurate readings, ensuring precise results even in diverse lighting conditions.

In summary, the development and implementation of currency detectors for individuals with visual impairments represent a significant stride toward building an inclusive and accessible society. By recognizing and addressing the specific needs of visually impaired individuals, we can ensure equal opportunities for full participation in all aspects of life.

To further enhance the effectiveness of fake currency detection systems, future endeavors should involve training models using image processing, pattern recognition, machine learning, or deep learning techniques. A comprehensive dataset comprising genuine and fake currency images should be utilized for robust training. The system should be capable of analyzing currency images and accurately classifying them as genuine or counterfeit, providing users with confidence in the authenticity of their currency. Additionally, integrating an inbuilt gesture mode would enhance interactivity and user experience.

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