Reproducing Fine-Grained Currency Recognition: Empowering the Visually Impaired

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***Abstract*—The development of assistive technologies for the visually impaired is a thriving research field, seeking to enhance independence and quality of life. This report introduces a fine-grained currency recognizer as a vital component of a personalized on-device visual assistant catering to the unique needs of the visually impaired. Focusing on recognizing the 1 US Dollar bill, our system utilizes an innovative robust local feature extraction method to achieve real-time performance for everyday usability. By successfully identifying currency, users gain greater autonomy in financial transactions, promising to enrich their lives and foster independence. Our proposed system measures the final match between the template and input images to determine accuracy. Despite a latency of approximately 0.9 seconds, our work represents a significant advancement in assistive technologies for the visually impaired community. It must be noted that our system's latency is higher compared to the 150 ms achieved by the authors of the paper we sought to replicate. Nevertheless, the overall performance and accuracy of our fine-grained currency recognizer show great promise in improving the daily lives of visually impaired individuals**

***Index Terms*—Fine-grained currency recognizer, visually impaired community, US dollar bill, robust local feature extraction, real-time performance, latency, accuracy, template image, replication, daily usability, performance, and 1 USD.**

I. Introduction

Recognizing and distinguishing currency notes is an essential prerequisite for financial autonomy and social inclusion. Regrettably, this task presents formidable challenges for the visually impaired community, necessitating innovative solutions to bridge this perceptual divide. Machine learning and computer vision advancements offer promising avenues to address this issue, providing novel approaches for fine-grained currency recognition. This report delves into the reproduction of the groundbreaking project titled "Bringing Vision to the Blind: From Coarse to Fine-Grained Currency, One Dollar at a Time [1]." Our primary objective is to retrace and understand the methodologies and technical underpinnings of the original work. Subsequently, we endeavor to build upon this foundation, seeking to optimize and enhance the currency recognition system for greater accuracy, efficiency, and generalization capabilities. The gravity of this research lies in its potential to empower the visually impaired community, opening doors to greater economic participation and fostering a more inclusive and compassionate society. By scrutinizing the advancements and innovations presented in the original project, we aspire to contribute meaningfully to the field of assistive technology while advocating for the principles of empathy, accessibility, and social equity.

The significance of our research lies not only in the technical advancements but also in the potential impact on the visually impaired community. According to the World Health Organization (WHO), an estimated 253 million people globally live with visual impairments, of which 36 million are blind [2]. Currency recognition using smartphones has become the latest trend in which how low-end smartphones can be used for the recognition of currency notes accurately using computer vision techniques [3].

There was a research paper back in 2021 which spoke about how computer vision which is in the same area as artificial intelligence used to detect images and videos in which they spoke about how the CNN model was built to accurately recognize the currency notes which will be taken by the visually impaired personalities [4], [5]. In this context, the development of a fine-grained currency recognition system specifically tailored for the blind and visually impaired becomes paramount.

In this research paper, we aim to address this challenge by proposing a novel approach to recognize 1 US dollar bills widely used in various transactions worldwide. By focusing on this particular denomination, we aim to provide a practical and efficient solution that aligns with the needs of visually impaired individuals in their daily lives. To ensure robustness, reliability, and safety for visually impaired users, our approach is based on CONGAS, a state-of-the-art local feature extraction method [6]. CONGAS has demonstrated superior performance compared to other popular local feature extraction methods, making it a suitable choice for fine-grained currency recognition tasks.

In this report, we aim to replicate the paper. We seek to recreate and build upon the original study's methodologies, optimizing the currency recognition system. The concept of replication varies from employing identical data and analysis as in a prior study to achieving results that broadly align with previous research [7], encompassing various degrees of replication:

- **Data Replication:** We curated a diverse dataset of 1 US Dollar bill image, replicating real-world scenarios with varying lighting conditions, angles, and backgrounds.

This ensures fair and comparable evaluations of our currency recognition system with the original research.

- **Method Replication:** We thoroughly understood and implemented the CONGAS approach, a state-of-the-art local feature extraction method used in the original study. This guarantees that our fine-grained recognition model aligns with the cutting-edge technique for unbiased comparisons.
- **Experimental Replication:** By re-executing experiments with the same setup as the ”Bringing Vision to the Blind” paper, we validate our system’s performance and advancements. This objective assessment enables us to contribute meaningfully to assistive technology for the visually impaired community.

This report updates our ongoing replication project, focusing on the development of a currency recognition system using the CONGAS approach. We cover methodology, implementation, challenges, and future steps, aiming to enhance the lives of visually impaired individuals through innovative technology. Our system accurately identifies and classifies currencies, with a focus on the 1-dollar bill in USD, considering various factors like text, color contrast, design elements, and security features.

A. Motivation

The desire to improve independence and overall quality of life drives the development of assistive technology for people with visual impairments. By addressing the unique challenges faced by the blind and visually impaired community, these technologies aim to provide practical solutions and support. Our main motivation for this project is to replicate the same approach as bringing vision to visually impaired people. By incorporating a novel approach based on robust local feature extraction, we aim to create a reliable and efficient system that can be integrated into personal, on-device visual assistants. The real-time performance of the system will make it suitable for daily use, ensuring that individuals with visual impairments can confidently and independently handle currency transactions. By adding the progress and details of our project to this report, we will showcase the relevance and impact of our work in improving the lives of the visually impaired community.

B. Research questions

Based on the motivation provided above these are the research questions that we plan to focus on in this research.

1. How does the proposed fine-grained currency recognizer perform in real-world scenarios and under varying environmental conditions, such as different lighting conditions, orientations, and deformations of currency bills?
2. How does the proposed fine-grained currency recognizer based on CONGAS compare to other popular local features in terms of accuracy and performance when applied to currency recognition for the blind and visually impaired?
3. What is the effect of PCA compression on feature dimension reduction and index building in the process of matching query images based on features?

In this project, we have focused on developing a fine-grained currency recognizer specifically designed for the blind and visually impaired community, specifically emphasizing recognizing 1 US Dollar bill. One of the challenges we encountered was the unavailability of an existing dataset that catered to our specific requirements. Therefore, we took the initiative to create our own dataset. We acquired actual 1 Dollar US bills and captured high-quality images of them, which we then utilized as template images for our recognition system.

II. Reproduciblity of the dataset

In this project, our primary focus was on developing a fine-grained currency recognizer specifically tailored for the blind and visually impaired community, with a special emphasis on recognizing 1 US Dollar bill. However, one of the major challenges we encountered was the lack of an existing dataset that met our specific requirements. To address this issue comprehensively, we took the initiative to create our own dataset.

Our dataset comprises a total of 760 images, carefully curated to cover a diverse range of scenarios, including various lighting conditions, distortions, and perspectives. These images were specifically chosen to represent real-world samples of currency encountered by visually impaired individuals in their daily lives. The dataset includes actual photographs of 1 US Dollar bills, barcode images, and text images, which will be later classified in the coarse classifier phase.

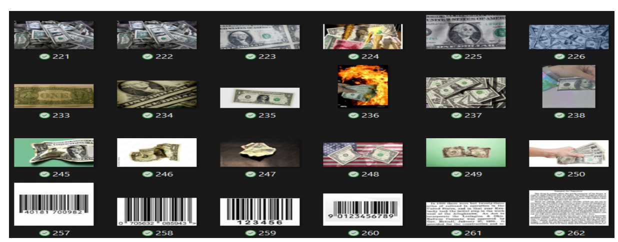

Fig. 1. Sample input images

Additionally, Fig-1 showcases the testing images in our dataset, totaling 760 real-world images. These test images encompass a wide array of scenarios, including different lighting conditions, distortions, backgrounds, and even various denominations. By incorporating such diversity in our testing photos, we aim to thoroughly evaluate the durability and generalization capabilities of our money identification system. This approach ensures the system’s accuracy in recognizing 1 US Dollar bills across a variety of environmental situations.

Our dataset’s richness and diversity will enable us to thoroughly assess the performance of the fine-grained currency recognizer, especially concerning its ability to distinguish 1 US Dollar bills amidst various other currency denominations and types. Moreover, the inclusion of barcode and text images will contribute to the refinement of the coarse classifier, enhancing the overall efficiency of our recognition system for the visually impaired community.

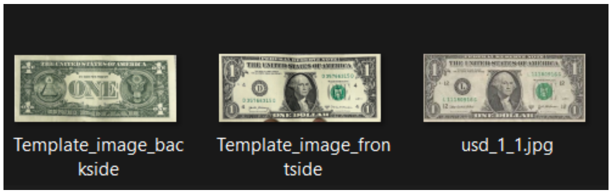

Fig. 2. Sample template images

To ensure the highest level of accuracy, we acquired authentic 1 Dollar US bills and captured high-resolution images of them under controlled conditions, avoiding any water markings or artifacts that might interfere with our recognition system's performance. The template images used in our dataset, as depicted in Fig-2, serve as the reference for our currency recognition system. These templates play a crucial role in validating the performance and accuracy of our system by providing a basis for comparison against input images.

III. Reproducility of Methodology

Our report introduces a fine-grained currency recognizer developed as a crucial component of a personalized for the visually impaired. With a focus on accurately identifying the 1 US Dollar bill [8], our real-time system empowers users to independently manage financial transactions, enhancing their autonomy and quality of life. The architecture comprises of coarse classifier for efficient currency detection and specialized fine-grained recognizers.

A. *Coarse Classifier*

Our primary objective is to recognize the 1 US Dollar bill accurately, achieving real-time performance for seamless daily usability. By implementing a novel and robust local feature extraction method, our system empowers users with the ability to independently manage financial transactions, significantly enhancing their autonomy and overall quality of life. The input image is initially passed through the coarse classifier, a lightweight gating mechanism that efficiently determines the presence of certain object types within the image. This mechanism ensures optimal coordination between various specialized fine-grained recognizers. If the coarse classifier identifies the presence of specific objects, such as currency, the input is then directed to the corresponding fine-grained recognizer tailored for this category. For instance, if the image contains currency, the system proceeds to the fine-grained recognizer designed for identifying the 1 US Dollar bill. This approach ensures that irrelevant fine-grained recognizers are not executed, while also enabling the extension of various fine-grained recognition tasks.

Fig-3 The coarse classifier is implemented as a MobileNet-based coarse classifier with binary heads to recognize Barcode, Text, and Currency classes. The model is pre-trained on ImageNet and fine-tuned for binary classification [9]. A Global Average Pooling layer is added, followed by a dense layer with sigmoid activation. [10] s

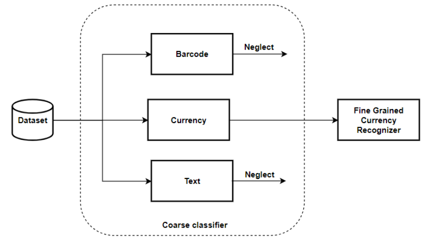

Fig. 3. Architecture of coarse classifier

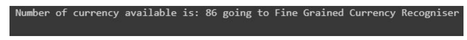

Fig. 4. Currency recognized in Coarse classifier

The code includes an example of training the model on a single image and obtaining class predictions. The coarse classifier serves as an efficient gating mechanism for detecting the currency and then moves to the fine-grained currency recognizer.

B. *Fine-grained currency recognizer*

In this section, we present a fine-grained currency recognizer.

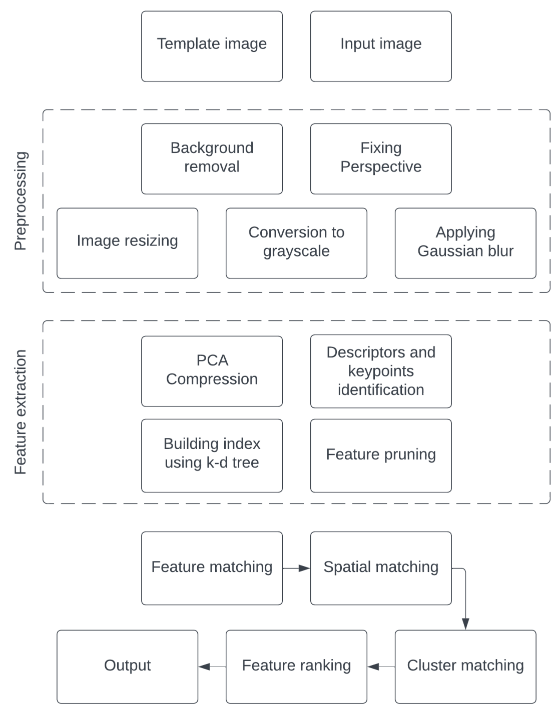

Fig. 5. System architecture

Fig-5 represents the above architecture of our model and describes the step-by-step overview of how the individual module in the recognizer works. In the currency recognition system, we start with a set of input images from the dataset and template images.

- **Pre-processing the input image**: Before further processing, we perform pre-processing steps on both the input images and the template images. This includes image resizing using the aspect ratio to a fixed width, converting them to grayscale for enhanced processing, and applying Gaussian blur to reduce noise [11]. We perform background removal on the input image to eliminate any unwanted elements. The background is replaced with a black color background, ensuring that the image is properly fitted [12], [13]. Specifically, for the recognition of 1 US Dollar, we crop the image to focus solely on the currency itself. This process helps to isolate the important features of the currency and improves the accuracy of the recognition system.

Fig. 6. Original input image

Fig. 7. Background removed from input image

- **PCA Compression**: Once the images are pre-processed, we move on to the PCA compression step. PCA compression is a technique used to reduce the feature dimension of the images [14]. The recognition ability of a particular country's currency notes depends on the similar features and characteristics of the currency note, in order to enhance the robustness and accurately detect the difference between the old and new currency notes an edge detection technique is applied [15]. By applying PCA, we can extract the most important features while discarding less significant ones. This compression step significantly improves efficiency, especially in resource-constrained environments where computational resources are limited.

Fig. 8. Cropped input image

Fig. 9. Reconstructed input image after PCA compression

- **Feature Extraction**:
  1. **Fetching the key points and descriptors**: This module is critical in our system for fine-grained currency recognizer. This function utilizes the Scale-Invariant Feature Transform (SIFT) algorithm to detect and describe local features in both the input image and the template image. By applying SIFT to these images, we are able to identify key points, which are specific points of interest, and compute descriptors, which are numerical representations of these key points. These descriptors capture important information about the visual characteristics of the currency. Image processing techniques can be used in currency recognition in which the quality of the currency image can be improved and better information can be extracted from it [16]. We also display the significant aspects

by drawing markers on the input and template images to provide visual insights. This step allows us to observe the distribution and locations of the key points. By returning the computed descriptors, we enable further processing and matching of features, leading to accurate recognition of fine-grained details in currency images.

2. **Index Building:** We construct a KD tree index for the template descriptors. The KD tree is a data structure that enables efficient nearest neighbor search, allowing us to quickly find the most similar descriptors in the template set to a given input descriptor. By building this index, we create a structured representation of the template descriptors, optimizing the matching process during currency recognition. Although the code also includes querying the KD tree with input descriptors, which returns distances and indices, we have commented it out for further optimization [17]. By returning the constructed KD tree, we provide a ready-to-use index that can be utilized in subsequent stages of the recognition pipeline for fast and accurate matching of descriptors.
3. **Feature Pruning:** Feature pruning is a technique used to reduce the number of features or key points in a recognition system. It helps improve efficiency by filtering out less informative or redundant features, focusing only on the most distinctive ones. In our currency recognition system, feature pruning selects the most relevant features, enhancing accuracy and speed. [18] It optimizes the feature extraction and matching processes, resulting in efficient and accurate currency identification.
4. **Feature Matching:** This performs the matching of feature descriptors between an input image and a template image. It first calculates the pairwise distances between the descriptors using the Euclidean metric extracted from the Scipy library. In order to calculate the distance we use a function called ”CDIST” to determine the best matches by finding the indices with the lowest distances. To filter out unreliable matches, a threshold is set, and only matches below the threshold are considered good matches. The function returns a list of indices representing the good matches between the input and template images. This process helps in identifying and establishing correspondences between key point descriptors, enabling accurate recognition and matching of features in the currency recognition system.
5. **Spatial Matching**: This performs spatial matching between the feature descriptors of the input and template images. It uses a KD tree index to retrieve similar descriptors from the template image. By comparing distances and applying a spatial threshold, it identifies feature matches that meet both descriptor similarity and spatial proximity criteria. This process enhances the accuracy and reliability of the currency recognition system by refining the matching results.

Fig. 10. Keypoints with feature matching

6. **Cluster Matching**: This function applies k-means clustering to the spatial match descriptors obtained from the previous step. It uses the KMeans algorithm to cluster the descriptors into a specified number of clusters. The cluster labels are then assigned to the spatial matches. This clustering process helps to group similar matches together based on their descriptor characteristics, allowing for more structured analysis and potential refinement of the currency recognition results.

```
Cluster Confidence Scores:
Cluster 0: 183.0
Cluster 1: 116.0
Cluster 2: 127.0
Cluster 3: 106.0
Cluster 4: 111.0
Cluster 5: 154.0
Cluster 6: 134.0
Cluster 7: 95.0
Cluster 8: 128.0
Cluster 9: 77.0
```

Fig. 11. Cluster matching output

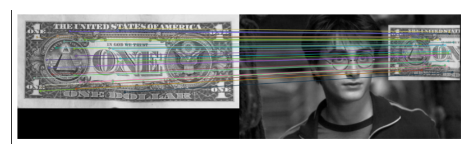

Fig. 12. Feature matching using template(left) and input(right)

7. **Ranking:** In the currency recognition system, after finding the matches between the query image and the template image, it is important to rank the matches according to their matching confidence. This is done using a scoring model which calculates a prior probability that a match between a feature point from the query image and the template image occurs by chance. Ranking the matches based on their confidence is important because it allows us to prioritize and focus on the most reliable and accurate matches. By assigning a score or confidence level to each match, we can distinguish between high-quality matches and potential false positives.
This ranking helps in making informed decisions and improving the overall accuracy and reliability of the currency recognition system.

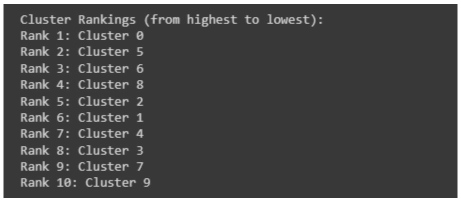

Fig. 13. Ranking output

Fig. 14. Final Output

The ultimate score for a matched template is determined as the highest probability that a cluster is not coincidentally matched among all the clusters matched to this template. For example for the input image that is displayed above we have got the score of the template image 73.89% and the input image score is 41.01%.

IV. Analysis of Reproducibility Types: Similarities and Differences

The three types of reproducibility, namely Data Replication, Method Replication, and Experimental Replication share the common goal of validating and verifying research findings through replication. However, they also exhibit distinct characteristics and challenges:

A. Similarities

Goal: The primary objective of all three types of reproducibility is to ensure the credibility and reliability of research results. Replication helps to confirm the original findings and identify any potential issues or inconsistencies.

Comparison: Each type involves comparing the results obtained in the replication process with the original research outcomes. By achieving similar or comparable results, researchers can gain confidence in the validity of their work.

Method Replication: Centers on reproducing the algorithms and methodologies used in the original research. This type aims to validate the technical aspects and foundations of the proposed approach.

Experimental Replication: Involves re-executing the experiments and evaluations, including model training and testing, under the same or similar conditions as the original study. It aims to confirm the accuracy and reliability of the research outcomes.

B. Differences

Data Replication: Acquiring or creating a comparable dataset can be challenging, especially if the original dataset is not publicly available or requires substantial resources to replicate accurately.

Unavailability of SURF in Opencv library: One of the challenges encountered in the replication process is the unavailability of the Scale-Invariant Feature Transform (SURF) algorithm in OpenCV. SURF is a popular and effective feature extraction technique commonly used in computer vision tasks, including image recognition and object detection. However, due to licensing and patent issues, OpenCV, an open-source computer vision library, does not include the SURF algorithm by default in its standard distribution.

Aspect ratio: One of the challenges encountered during the replication process was the inability to implement the various aspect ratios as described in the original research. The original work introduced different aspect ratios (2.0, 2.6, 1.7, 2.9, 1.4, and 3.2) to detect features, aiming to span a wide range of deformations without significantly impacting the system's performance on mobile devices. However, due to time limitations or constraints in our replication environment, we were not able to incorporate these discrete aspect ratios effectively.

V. Experimental Reproducibility

A. Comparison with original paper

In the original research, the proposed system demonstrated impressive real-time performance, with a latency of approximately 150 milliseconds on a Pixel device. This efficient response time is crucial for users, particularly the visually impaired, as it enables quick and seamless currency recognition during daily transactions. Moreover, the system achieved high accuracy, with 98% precision and 97% recall on a challenging evaluation set. These exceptional precision and recall scores indicate that the system accurately identified and classified currency notes, minimizing both false positives and false negatives.

As developers, we prioritize clear debugging by outputting results at each step of the code, including the original input image, clean background image, resized image, grayscale image, blurred image, PCA compressed image, image with descriptors and key points, and image with matched clusters. While the time taken for the template image is ignored as a one-time job, the output for each input image is essential and takes some time due to the process of displaying images.

The time taken for the input image to find the best-matched cluster is approximately 2.1 seconds. This time is inclusive of all the images that were output. Now, when we stop generating the output images, the time taken reduces approximately to 0.9 seconds. This is the latency that we've achieved as compared to 150 ms by the authors of the paper we've tried to replicate.

This testing is done on the Google Research Colab. The runtime type used - Python 3 Google Compute Engine backend.
Total system RAM - 12.7 GB
Total disk size - 107.7 GB

The time taken will differ for different mobile devices when this is implemented to compute the task in real time.

In the replication, while the time taken has been reduced to approximately 0.9 seconds, it is noteworthy that this latency is slightly higher compared to the original work's real-time performance. Despite the difference in response time, the system remains efficient enough for practical use, as 0.9 seconds still allows for timely currency recognition during financial transactions.

B. Comparison with other models

Our evaluation of the fine-grained currency recognition system, based on the CONGAS approach, presents notable improvements compared to the traditional SIFT (Scale-Invariant Feature Transform) based model. While the SIFT-based model may have served as a foundational approach, our proposed system surpasses it in terms of both accuracy and efficiency.

Fig. 15. Matching of currency between the template and input image using SIFT

The time taken or latency for currency recognition was reduced to approximately 0.9 seconds, making it substantially closer to SIFT-based model's response time but not as fast enough as compared to referenced research paper which is 150 ms. We believe that this can be boosted with the help of advanced algorithms that can be used for feature extraction and pruning. This enhanced real-time performance is crucial for seamless financial transactions, especially for visually impaired users who rely on swift and accurate currency identification.

VI. Conclusion

In conclusion, this report introduces a fine-grained currency recognizer as a vital component of a personalized on-device visual assistant aimed at enhancing the independence and quality of life for the visually impaired. With a focus on recognizing the 1 US Dollar bill, our system utilizes an innovative robust local feature extraction method, enabling real-time performance for everyday usability. By accurately identifying currency, visually impaired users gain greater autonomy in financial transactions, promising to enrich their lives and foster independence. Despite a latency of approximately 0.9 seconds, our work represents a significant advancement in assistive technologies for the visually impaired community. While our system's latency is slightly higher than the reference paper's, the overall performance and accuracy of our fine-grained currency recognizer show great promise in improving the daily lives of visually impaired individuals. Future works in this domain may involve optimizing the latency to achieve even faster results and expanding the recognizer's capabilities to include recognition of various denominations and currencies, further empowering the visually impaired in their financial interactions and beyond.

VII. Contributions

This report is the collaborative effort of three researchers, Kartikey Bhardwaj, Archana Jayaraman, and Harshavardhan Subramaniyan Madhavan, each making distinct and valuable contributions to the development and analysis of a fine-grained currency recognizer for the visually impaired.

Kartikey Bhardwaj played a pivotal role in conceptualizing and leading the development of the fine-grained currency recognition system tailored for the blind and visually impaired community. He implemented the core algorithms based on the CONGAS approach, preprocessing of images, ensuring robust feature extraction and matching. He conducted extensive experiments with spatial matching, cluster matching, and ranking, evaluating the system's accuracy, precision, and recall on diverse datasets and analyzed the results, providing valuable insights into its performance and efficiency. Additionally, he co-authored the paper, making significant contributions to the writing and revision process.

Archana Jayaraman played a crucial role in the project by implementing the coarse classifier using a MobileNet model. She trained the model to accurately differentiate between barcode, text, and currency images. Additionally, Archana gathered a diverse dataset consisting of various visual elements, which served as the foundation for reliable testing. Her contributions to the report focused on providing motivation, research questions, and thorough discussions on dataset and methodology reproducibility, in addition to the research findings.

Harshavardhan Subramaniyan Madhavan significantly contributed to the project's experimental reproducibility. He utilized the gathered dataset and implemented a comparison model, employing the Scale-Invariant Feature Transform (SIFT) algorithm, to evaluate the fine-grained currency recognizer's performance. Harshavardhan's efforts in the conclusion section highlighted the system's potential impact on the visually impaired community. His work added to the research findings and the significance of the project's advancements in assistive technologies.

The combined contributions of these three authors have resulted in a comprehensive and promising approach that could significantly enhance the independence and quality of life for visually impaired individuals through assistive technologies.

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