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Currency Recognition for Visually Impairment People Using Deep Learning Algorithm

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ABSTRACT- *Currency recognition for blind people is an important issue as it allows them to independently manage their finances and enhance their daily lives. In this project, a novel system is proposed for currency recognition using computer vision and machine learning techniques. The system utilizes a camera and image processing algorithms to extract features from banknotes and classify them according to their denomination. Currency recognition technology can greatly benefit visually impaired individuals by providing them with the ability to manage their finances independently. Blind people often face challenges when it comes to managing their money, as they cannot distinguish between different denominations of banknotes. This technology can empower them to confidently identify and manage their money, enhancing their daily lives and improving their financial independence. In addition to helping blind people, currency recognition technology can also benefit other individuals and organizations, such as banks, retailers, and vending machine operators. These entities can use this technology to automate their processes and improve the efficiency of their operations. Convolutional Neural Network (CNN) is a deep learning algorithm that is widely used in image recognition and computer vision applications. CNN has been shown to achieve high accuracy in recognizing complex patterns and features in images, making it an ideal algorithm for currency recognition for blind people. To implement currency recognition using CNN, the system would first need to collect a large dataset of banknote images of different denominations. The images would then be pre-processed, which could involve resizing, normalization, and other transformations to improve the quality of the data. The CNN would then be trained on the pre-processed images, with the goal of learning the underlying patterns and features that differentiate one banknote denomination from another. The training process would involve forward and backward propagation of the data through the network, with the weights and biases of the filters being updated at each iteration to minimize the error between the predicted and actual denominations.*

KEYWORDS: *Currency Recognition, Deep learning, Convolutional neural network, Blind people, Machine learning*

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I. INTRODUCTION

Currency recognition is not only important for financial independence but also for safety. Blind individuals are vulnerable to fraud and theft as they cannot visually inspect the notes they receive. Accurate and reliable currency recognition solutions can help prevent such instances, ensuring that blind individuals can handle their finances with confidence and security. Tactile markings and mobile apps have been widely adopted and are easily accessible for blind individuals. However, these solutions can be limited in certain situations, such as when the user does not have access to a mobile device or when the tactile markings are not universally adopted. Smart devices and innovative solutions, such as India's rectangular identification mark, can provide more comprehensive solutions for currency recognition. It is important to note that while technology-based solutions can be useful, they may not always be affordable or accessible to everyone. Governments and financial institutions should prioritize the development and implementation of universal solutions that can be easily adopted by all individuals with visual impairments, regardless of their socioeconomic status.

Currency recognition is just one aspect of financial accessibility for blind individuals. In addition to recognizing currency, it is important to ensure that financial institutions and services are designed to accommodate the needs of individuals with visual impairments. This includes accessible ATMs, online banking platforms, and customer service that is trained to provide assistance to blind individuals.

Another important consideration in currency recognition for blind individuals is the ability to handle and distinguish coins. Unlike paper currency, coins do not have as much space for tactile markings, and their sizes and shapes can vary widely. Some coins may have raised edges or engravings to help with identification, but these features can be difficult to distinguish by touch alone.One solution for coin recognition is the use of electronic devices that can identify and count coins. These devices can use sensors or cameras to detect the size, shape, and weight of coins and provide audio or visual feedback to the user. For example, the Royal National Institute of Blind People in the UK has developed a device called the "Talking Coins" that can recognize and count UK coins and provide audio feedback to the user. However, like other technology-based solutions, these devices may not be affordable or accessible to everyone. Governments and financial institutions should consider incorporating features that make coins more accessible for blind individuals, such as larger sizes, different textures, or more distinct shapes. Another consideration in currency recognition is the need for training and education for blind individuals. While technology-based solutions can be helpful, they require some level of technical proficiency, which may not be available to everyone. Institutions should provide training and support to ensure that blind individuals can effectively use these solutions and manage their finances independently.

Fig 1: Currency datasets

II. RELATED WORK

Wei sun, et.al,…[1] proposed a lightweight neural network model based on dilated convolution and depth wise separable convolution with twenty-nine layers for image classification. The proposed model employs the dilated convolution to expand the receptive field during the convolution process while maintaining the number of convolution parameters, which can extract more high-level global semantic features to improve the classification accuracy. Also, the depth wise separable convolution is applied to reduce the network parameters and computational complexity in convolution operations, which reduces the size of the network. The proposed model introduces three hyperparameters: width multiplier, image resolution, and dilated rate, to compress the network on the premise of ensuring accuracy. For that purpose, the YOLO-v3 CNN model-based banknote detection and recognition system is proposed which is fast and accurate. Images of different denominations and in different conditions were are collected initially and then, these images are augmented with different geometric and image transformations on images, to make the system robust. These augmented images are then annotated manually, from which training sets and validation image sets are prepared. Later, the performance of the trained model has evaluated on a real-time scene as well as a test dataset.

Rushikesh jadhav, et.al,…[2] facing the currency recognition problem due to the fake denominations in the market or illiteracy of the people in the given country, so automatic currency recognition system is important. Accuracy and speed are the two important factors in such a system. Also, accuracy is more important than speed. A currency recogniser recognises the currency and identifies denomination by analysing the prominent attributes. Researchers proposed so many methods. Some of them use physical properties (width, length) and few uses internal properties (texture, colour). In the software field every problem has a solution. Using such software solutions, we can save our time as well as energy. In the early 90's there was one method which identified currency notes using image processing. However, their algorithm does not take aspects of authentication of the notes into account. For such a system it was necessary to have an input of the image after that it was performing some tasks over to it. Great advancement of the technologies in the banking sector has resulted in the introduction of self-servicing for making transactions simple and friendly to the customers. also, we are known with the currency counting machines where this currency recognition technique is used. New techniques related to the recognition are also introduced by these banks like cash deposit by the user itself through the machines without visiting the respective bank. Here currency recogniser is required to check currency and handle it according to the denominations.

Chanhum park, et.al,…[3] studies on banknote detection, high detection performance was observed by applying speeded-up robust features (SURF) to the banknotes. However, the performance of SURF was significantly degraded when the images captured in complicated and diverse backgrounds were used. In other research, the classification of fake banknote using deep learning was proposed, which did not require the pre-classification of banknote images in the denomination and input direction. However, the regions of banknotes were manually segmented from the input image, which requires user's assistance to use this method in actual smartphone. In addition, most previous studies on banknote detection using deep learning have used databases with simple backgrounds or with the application of a slight rotation such that the objects can be easily recognized. Thus, the studies that examine the detection performance using the images captured in various conditions are lacking. Owing to the rapid advancements in smartphone technology, there is an emerging need for a technology that can detect banknotes and coins to assist visually impaired people using the cameras embedded in smartphones. However, these studies also showed degraded performance depending on the changes in background and environment. To overcome these drawbacks, this paper proposes a three-stage detection technology for new banknotes and coins by applying faster region-based CNN, geometric constraints, and the residual network (ResNet).

Tuyen danh pham, et.al,…[4**]** include the recognition of the banknote type and denomination, counterfeit detection, fitness classification, and serial number recognition, which are mostly conducted on automated transaction facilities, such as counting machines or vending machines, based on image processing techniques. Among these tasks, counterfeit detection plays an important role in ensuring the security of transactions because fake bills still exist at various sophisticated levels. Anti-counterfeit technologies, which are now being applied to banknotes in general, consist of various features, such as security threads, anti-copier patterns, watermarks, or hologram patterns. However, the frequent check of counterfeit notes is difficult owing to the large number of bills in recirculation and the complexity of the detection techniques, which involve various detection sensors, such as magnetic, infrared (IR), or ultra-violet (UV) sensors. As a result, it is difficult for general users to check for counterfeit banknotes. Automatic recognition of fake banknotes is an important task in practical banknote handling. Research on this task has mostly involved methods applied to automatic sorting machines with multiple imaging sensors or that use specialized sensors for capturing banknote images in various light wavelengths. These approaches can make use of the security features on banknotes for counterfeit detection. However, they require specialized devices, which are not always available for general users or visually impaired people. Meanwhile, smartphones are becoming more popular and can be useful imaging devices.

Rakesh chandra joshi, et.al,…[5] developed for healthcare services in the last decade. The aim of these advancements is to reduce the cost of the medical diagnosis and to assist the health sector with technology where a person can self-manage the things easily as never before without having the direct supervision from the specialist. However, the people having disabilities were not the primary target of these kinds of advancements. However, there is an urgent need for technologies, which can help and assist in day-to-day lives and can better their living in a simple manner and lead a way to independence. Out of these disabilities, Visual Impairment is much significant. Currencies play an important role as a medium for a transaction to have goods and services. Every country has their own currency in different denominations, which differs in color, size, shape, and pattern. It becomes very difficult for any visually impaired to recognize and count the currency in different denomination. Tactile marks at the banknote's surface vanish or faded away due to continuous use, which suffers visually impaired people to detect and identify banknotes properly by means of touch. The digital image processing is a broad area, which gives the solution to these kinds of problem, where searching and extraction of the patterns as well as identification marks is performed and then match those with original banknotes images.

III. BACKGROUND OF THE WORK

In currency recognition using machine learning, there are some challenges that need to be addressed. One of the challenges is the variability in the appearance of currency due to different orientations, lighting conditions, and backgrounds. To address this challenge, data augmentation techniques can be used to create additional images with different orientations and lighting conditions. Another challenge is the presence of counterfeit currency, which can be difficult to distinguish from genuine currency. To address this challenge, the model can be trained on both genuine and counterfeit currency images to improve its ability to differentiate between them. Dense Connection, Multi-Dilation, and Depth-wise Separable Convolution layers are all advanced techniques in convolutional neural networks (CNNs) that can improve the accuracy of currency recognition. Dense Connection layers, also known as DenseNet, allow for a more efficient flow of information between layers in a CNN. Traditional CNNs have a series of layers that extract features from the input image and pass them on to the next layer. Multi-Dilation layers, also known as Dilated Convolution, allow for a larger receptive field in CNNs without increasing the number of parameters. Traditional CNNs have a fixed receptive field, which is the area of the input image that a single neuron in the network is sensitive to. Multi-Dilation layers allow for multiple dilation rates, which means that a single neuron can be sensitive to a larger area of the input image. Traditional convolutional layers perform both operations simultaneously, which can be computationally expensive. Depth-wise Separable Convolution layers first apply a spatial convolution to each channel of the input data, and then apply a point-wise convolution to combine the channels. This reduces the number of computations required, making the model more efficient.

IV. PROPOSED WORK

The proposed system for currency recognition using Convolutional Neural Networks (CNNs) would start with the collection of a large dataset of labelled currency images that includes different currencies, denominations, orientations, and lighting conditions. The data would then be pre-processed by removing noise, resizing the images, and normalizing the pixel values. The pre-processed data would then be split into training, validation, and test sets. The CNN model would be designed with multiple convolutional layers, each followed by a pooling layer to reduce the spatial size of the output feature maps. The design would also include Dense Connection, Multi-Dilation, and Depth-wise Separable Convolution layers to improve the accuracy of the model. The output of the convolutional layers would be flattened and passed through fully connected layers to produce the final output. The model would be trained on the training dataset using backpropagation and gradient descent to optimize the weights of the network. During training, the model would also perform data augmentation to increase the size of the training dataset and improve the generalization of the model. After training, the model would be evaluated on the validation set to adjust the hyperparameters of the model such as learning rate, dropout rate, and number of filters in each layer. Finally, the model would be tested on the separate test dataset to measure the accuracy, precision, recall, and F1 score. Once the model has been trained and evaluated, it can be deployed in a production environment where it can be used to recognize currencies in real-time. The system can be integrated with various applications such as ATMs, cash counting machines, and vending machines to automate currency recognition and improve the efficiency of cash transactions.

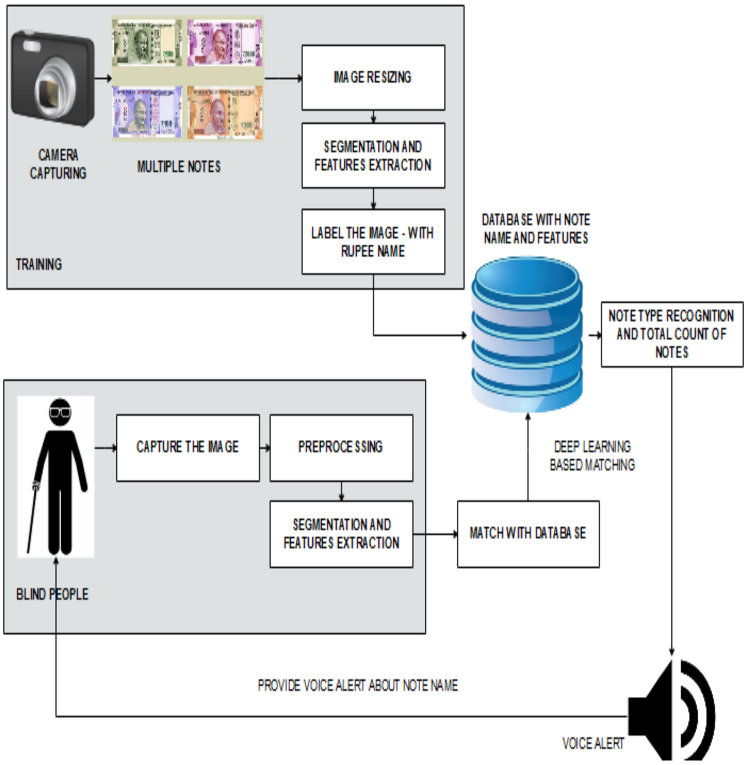

Fig 2: System Architecture

In training phase, train the image datasets and extract the features using Convolutional neural network algorithm. Then testing phase, input the image or capturing the image from user. Then extract the features using CNN algorithm. Finally classify the image to recognize the currency and provide voice alert about currency. And also, denominations about the notes.

4.1 IMAGE ACQUISITION

In this module, user can input the currency note. Input may be in the form of image or camera capturing. Currency may differ in terms of color, shape and other features. The Indian Currency Dataset is a publicly available dataset that consists of images of Indian currency notes of different denominations. The dataset includes a total of 6000 images, with 1000 images for each denomination of 10, 20, 50, 100, 200, 500, and 2000 rupees. The images were captured using different cameras and lighting conditions, which makes the dataset more diverse and challenging. The dataset also includes images of both sides of the currency notes, which provides additional information to the machine learning models. The dataset is labeled with the denomination of each currency note, which makes it suitable for supervised machine learning algorithms. The dataset is commonly used for training and evaluating machine learning models for currency recognition tasks. The Indian Currency Dataset is a valuable resource for researchers and developers working on currency recognition applications in India. It provides a realistic and diverse set of images that can help improve the accuracy and robustness of machine learning models.

4.2 PREPROCESSING:

Pre-processing in images refers to the steps taken to prepare an image for further analysis or processing. This often involves cleaning, transforming, and normalizing the image data to improve the quality and make it more suitable for various image processing tasks. Common pre-processing techniques include cropping, resizing, noise reduction, histogram equalization, normalization, and others. The specific techniques used depend on the task and the type of image being processed. Preprocessing is an essential step in currency recognition to improve the quality of the input data and enhance the accuracy of machine learning models. Here are some common preprocessing steps for currency recognition:

- Image resizing: The first step in preprocessing is to resize the images to a standard size. This is important to ensure that all images have the same dimensions and aspect ratio. This can help reduce the computational complexity of the model and improve its efficiency.
- Normalization: Normalization is the process of adjusting the pixel values of the image to a standard range. This can help improve the contrast and brightness of the image and make it easier for the model to learn important features.
- Noise removal: Currency images often contain noise and artifacts that can interfere with the model's ability to recognize important features. Noise removal techniques such as Gaussian smoothing, median filtering, or image thresholding can be used to remove noise and improve the quality of the images.

4.3 SEGMENTATION AND LABELING:

In this module, implement to predict the contour of the note. Using features extraction algorithm to extract the color and shape features based on geometrical features. Finally extract the text details using Convolutional neural network algorithm. Convolutional neural networks (CNNs) have proven to be highly effective in currency recognition tasks, as they can extract discriminative features from input images that can be used for classification. The first step in using a CNN for feature extraction is to normalize the pixel values of the input images to a standard range. This is typically done by dividing the pixel values by 255, which scales the values to between 0 and 1. The next step is to feed the normalized images into the CNN. The CNN typically consists of multiple layers of convolutional, pooling, and activation functions that learn and extract features from the input images. The convolutional layers use filters to scan the input images and extract features at different scales, while the pooling layers down sample the feature maps to reduce their dimensionality. The activation functions introduce non-linearity into the model, which enables it to learn more complex features. Once the input images have been processed by the CNN, the resulting feature maps are flattened into a 1D vector and fed into a fully connected layer. This layer acts as a classifier and maps the features to the different currency denominations. The output of the classifier is a probability distribution over the different classes, which can be used to predict the denomination of the input currency note. Overall, CNNs have proven to be highly effective in currency recognition tasks due to their ability to learn discriminative features from input images. By normalizing the input images and applying a series of convolutional, pooling, and activation functions, the CNN can extract and learn features that are highly relevant for currency recognition.

4.4 CAMERA CAPTURING:

Blind people can be difficult to recognize the bank notes. In this module, blind people can be capturing the image through camera. Image can be any type or size. Image can be set the predefined size for future analysis. Camera capturing is an important aspect of currency recognition as it involves capturing images of currency notes that will be used as input for machine learning algorithms. The quality of the images captured can significantly affect the accuracy and reliability of the currency recognition system. When capturing images of currency notes, it is important to consider the lighting conditions and the angle of the camera. Uneven lighting or shadows can create unwanted artifacts or noise in the images, while capturing the image from an angle can cause distortion in the shape of the currency note. It is recommended to capture images of currency notes in a well-lit environment, using a camera with a high resolution and good color accuracy. The camera should be positioned directly above the currency note to avoid distortion, and care should be taken to ensure that the note is flat and not crumpled or folded. To ensure consistency in the images captured, it is recommended to use a standard background and a fixed camera position. This can help reduce variations in the images and make it easier for the machine learning algorithms to learn the features that are relevant for currency recognition.

4.5 NOTE CLASSIFICATION:

In this module, implement deep learning algorithm to classify the notes. Based on features, matched with database for detect the types of notes. And also predict the currency information based on features. In deep learning, including convolutional neural network algorithm to improve the accuracy. Currency notes classification using CNNs is a process that involves training a model to classify different denominations of currency notes based on their image features. The first step in this process is to prepare a dataset of labeled currency note images for training and testing the model. The dataset should be divided into training and testing sets, and it should include images of each denomination. Next, the CNN architecture is defined, typically consisting of multiple convolutional layers followed by pooling layers, and a fully connected layer for classification. The model is then trained on the training set using backpropagation and gradient descent optimization to adjust the weights of the CNN and minimize the loss between the predicted and actual labels. Once the model is trained, it is tested on the testing set to evaluate its performance on unseen data. The accuracy of the model is calculated based on the number of correctly classified images. If the performance of the model is not satisfactory, it can be fine-tuned by adjusting the parameters or hyperparameters of the CNN. Overall, CNNs have been shown to be highly effective in currency note classification tasks due to their ability to learn discriminative features from input images. By training a CNN on a dataset of labeled currency note images, it is possible to develop an accurate and reliable currency recognition system that can be used for a variety of applications.

4.6 VOICE ALERT:

In this module, types of notes can be converted into voice. Blind people easily recognize the note without any sensors and assistants. A voice alert system can be implemented in a currency recognition system to notify the user about the denomination of the recognized note. After the currency note image is captured and processed using CNNs for classification, the output of the classification can trigger a pre-recorded voice alert corresponding to the denomination of the recognized note. The implementation of a voice alert system can add an additional layer of accessibility and user-friendliness to the currency recognition system. It can also help increase the system's usability in various settings, such as in retail stores, banks, or vending machines.

V. CONCLUSION

The implementation of a voice alert system can add an additional layer of accessibility and user-friendliness to the currency recognition system. It can also help increase the system's usability in various settings, such as in retail stores, banks, or vending machines. In addition to providing a useful tool for blind individuals, currency recognition systems can also have practical applications in various industries. For instance, banks, retail stores, and vending machines can benefit from currency recognition systems in streamlining their operations and reducing the risk of errors or fraudulent activities. Currency recognition systems can also help governments and financial institutions in tracking and monitoring the circulation of currency notes. By accurately identifying and classifying different denominations of currency notes, it becomes easier to trace the movement of money, prevent counterfeiting, and identify patterns in cash flow. However, developing a robust and reliable currency recognition system requires careful consideration of various factors, including the quality of image capture, the choice of machine learning algorithm, and the diversity and size of the training dataset. Additionally, currency recognition systems must be designed with user privacy and security in mind, as they involve handling sensitive financial information.

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