IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 3, May 2023

Currency Recognition for Visually Impairment People using Deep Learning Algorithm

Aarthy. R[1], Arunkumar Ramachandiran[2], Ayyanar Ramasamy[3], Dhanush Maniyarasu[4], Murugan Magaraja[5].

Assistant Professor, Department of Computer Science and Engineering[1]

Students, Department of Computer Science and Engineering[2,3,4,5]

Dhanalakshmi Srinivasan Engineering College, Perambalur, India

Abstract*:* *Since technology enables blind individuals to independently handle their finances and improve their everyday lives, currency recognition is a crucial topic. This research proposes a revolutionary system for recognising cash using computer vision and machine learning methods. The system extracts information from banknotes and categorises them based on their denomination using a camera and image processing algorithms. People who are visually blind can greatly benefit from currency recognition technology by being able to freely manage their finances. Blind people frequently struggle with managing their finances because they are unable to discern between different cash denominations. By enabling individuals to reliably identify and handle their money, this technology can improve their daily lives and financial independence. Currency recognition technology can assist those who are blind as well as other people and organisations, including banks, shops, and vending machine owners. These organisations can automate their procedures and increase the effectiveness of their operations by using this technology. Deep learning algorithms like the Convolutional Neural Network (CNN) are frequently used in computer vision and image recognition applications. CNN is a perfect algorithm for cash recognition for blind individuals because it has been demonstrated to attain great accuracy in recognising complex patterns and characteristics in images. The system would first need to gather a sizable collection of banknote images of various denominations in order to conduct currency recognition using CNN. In order to enhance the quality of the data, the photos would subsequently undergo preprocessing, which might include scaling, normalisation, and other changes. The preprocessed photos would then be used to train the CNN, with the intention of teaching it the underlying patterns and features that distinguish one banknote denomination from another. In order to reduce the error between the anticipated and actual denominations, the training procedure would comprise forward and backward propagation of the data through the network, with the weights and biases of the filters being modified.*

Keywords: CNN, Deep Learning, Image Processing, ML, ANN

I. INTRODUCTION

Currency identi forth in is an essentiabe piece of technology that helps people with visual impairments recognise various coin denominations. The user of the currency's denomination is sent through a range of audible or tactile signals using this technology. With the use of tools like cell phones, cameras, and specialised software that can scan banknotes and identify them, people can conduct financial transactions with ease and trust .This paper suggest same thod for cash recognition using image processing. This method relies on three characteristics for recognition: colour, size, and text ure. The method put forth in this paper cane used to identify many different national currencies. Only paper currencies from India are taken into consideration for implementation purposes. This technology makes it simpler to check the value of money at any time and any where and it uses the CNN (convolutional neural network) [1].This technology has become increasingly important because cash is still a vital means of payment in many countries throughout the world. Routine financial tasks may be challenging for those with vision impairments. To recognise photos, faces, car licence plates, and human behaviours nowadays, a variety of recognition techniques are used. Currency is the main unit of measure for circulation, and different currencies have different characteristics. Therefore, there will be more counterfeit money available as the value of cash rises. The interests of these countries may be harmed by counterfeit money. How to employ identification technology to verify the legitimacy of money is therefore one of the hottest topics and a crucial concern at the moment.[2].Due to their inability to differentiate between various banknote denominations, they are unable to perform tasks, such as paying bills, making purchases, or withdrawing money from an ATM. However, they can be time consuming, uncomfortable, and jeopardise the user's privacy. Two typical conventional methods of recognising banknotes include asking sighted individuals for assistance or employing tactile markers. In money identification technology, sophisticated algorithms and machine learning techniques are utilised to identify the different features of various banknotes, such as size, colour, texture, and patterns .Because the technology can be included into so many various products, like as smartphones, wearables, and standalone gadgets, users can readily access and use it. As currency recognition technology enables blind or visually impaired persons to manage their money independently, it boosts their self confidence and improves their quality of life. It also encourages financial inclusion by reducing barriers that prevent persons with disabilities from getting essential financial services and participating in economic activity with every iteration.

Figure1: (a) Ten Rupees Indian Currency

Figure 2:(b) Fifty Rupees Indian Currency

Figure3:(c) Hundred Rupees Indian currency Figure 4:(d) Two Hundred Rupees Indian Currency

Figure 5:(e) Five Hundred Rupees Indian Currency **Figure5:(f) Two Thousand Rupees Indian Rupees**

II. RELATED WORK

A normal person can detect and identify any banknote with ease, while a blind or visually impaired person finds it very difficult to perform the sameactivity.As money plays a crucial rolein daily life and in all economic transactions, realtime detection and recognition of banknotes are essential for everyone, but notably for individuals who are blind or visuallyimpaired.It could be used for a variety of things, such as electronic banking, cash identification technology, and money exchange of the existingequipment.[3]For this, the rapid and accurate YOLOv3 CNN modelbased banknote

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 3, May 2023

detection and recognition system isrecommended.Images from many faiths and environments were initially gathered to reinforce the system, and these photos were then enhanced with numerous geometric and aestheticadjustments.Training sets and validation picture sets are produced after manually annotating these improvedphotos.Later, the trained model's performance was assessed using a realtime scene and a testdataset.According to the test findings, the proposed YOLOv3 modelbased technique has detection and recognition accuracy of 95.71% and 100%, respectively.The whole thing runs autonomously and in real-time.[4]

By identifying the reverse motifs various objects, persons, scenes, animals, and buildings along with legends,we can classify ancient Roman Republican coins. Due to their age and different levels of preservation, the majority of these coins have deteriorated, which affects their informative qualities for visual identification. Huge differences between coin types are also brought on by adjustments to the primary symbolplacementsonthereversepatternsLast but not least, in plane orientations, uneven lightingand moderate backdrop clutter add to the difficultyof the categorization assignment.In order to achieve this, we introduce CoinNet, a unique network model that makes use of layers of feature attention, residual groups, and compact bilinearpooling.Democraticcoins.Additionally, we gathered the largest and most varied picture library of Roman Republic coins, which consists of more than 18,000 photos with 228 distinct theme types.On this dataset, our model beats both traditional bagofvisualwordsbased approaches and more modern stateoftheart deep learning techniques, achieving a classification accuracy of more than98%.We also give a thgh analysis of our network's capacity to generalise through ablation. [5]

Visual object detection and recognition have greatly benefited from deep learning.Fastmoving object recognition from t he perspective of computer vision is still a difficult problem.Recurrent neural networks (RNN) are ideal for representin g the properties of object motion in deep learning, and their Long ShortTerm Memory (LSTM) model is best for recogn ising objects that move quickly.As a result, the LSTM and CNN combination completely exploit the spatial and tempor al characteristics of movingobjects.In this study, we use deep learning techniques, particularly those based on the combi nation of LSTM and CNN, to identify fastmoving coins from digital films.We achieve fastmoving coin detection with h igh accuracy using the suggested strategy, outperforming our human visual system.[6]

Convolutional neural networks (CNNs), in particular, have recently been applied in some cuttingedge efforts for bankn ote recognition and counterfeit detection,with promising results.For huge data applications, is unclear which design stra tegycustom orransfer learningis better in terms of classifier performance and ne times.In this essay, the two design appr oaches are contrasted in relation to various types of architecture.The best freezing points in CNN architectures (sequenti al, residual, and inception)are determined using the transfer learning (TL) technique.Additionally, a unique model built on a sequential CNN similar to AlexNet is suggested.Using a dataset of Colombian banknotes, the TL and the custom models weretrainedand contrasted.The results show that ResNet18 had the highest accuracy, at 100%.The proposed cus tom network, on the other hand, had the fastest inference times since its performance was up to 6.48 times quicker on th e CPU and 16.29 times faster on the GPU than the inference time using the transfer learning The results show that ResNet18 had the highest accuracy, at 100%. The proposed custom network, however, had the quickest inference times because of its up to 6.48 times higher CPU performance and 16.29 times faster transfer learning performance.[7]

In this research, we provide an automated approach for recognising currencies using image processing methods.The sug gested technique can be used to identify a given banknote's country of origin, denomination, and value.Only paper mon ey has been taken into account.Depending on how much the notes from the same country differ from one another, this method works by first identifying the country of origin using specific predetermined regions of interestand then extracti ng the denomination value using attributes such as size, colour, or writing on the note.We have taken into account the d enominations of 20 of the most popular currencies.Our system can rapidly and precisely locate test notes.The sight-impaired person faces a number of major problems, including money and,notably,money recognition. However, a person who is weak on the outside may not understand the value of money, and they frequently deal with problems relating to the exchange of money. To solve this problem, we have created a system for accepting cash and notes, which could be a useful tool for someone who is physically weak. Investigations and tests were conducted on the informative money collection, which influenced CNN's reliance on important features. uchas watermarks, images printed on money, esteemed compositions as words and numbers, and the overall amount of money The use of convolutional neural networks (CNNs) to address societal problems and research into the presentation and assessment of various CNN models are the main topics of this study. Alexnet, Googlenet, and Vgg16 models have been taken into consideration in

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 3, May 2023

this analysis. Each model was modified in terms of how the various data sets were created and tested. In terms of preparation, Alexnet outperformed the other two models (the VGG16 model showed greater execution and achieved 100%, while Google Net comes in at 88% in terms of productivity). [8]

III. DATASET

Images of Indian rupees make up the dataset, which was collected from free online resources like Kaggle.It is a representation of Indian banknotes.Each of the twofolders,trainingandvalidation,hassevenclasses. 26 imag es are in eachclass.There are atotalof12images. There were 87 images in the 10 rupee class, 75 in the 20 rupee class, 79 in the 50 rupee class, 91 in the 100 rupee class, 84 in the 200 rupee class, 84 in the 500 rupee class, and 84 in the 2000 r upee class 584

IV. MODEL ARCHITECTURE

System architecture is the conceptual layout of a hardware or software system that identifies the various parts, modules, and connections between them.It offers a highlevel overview of the system, its features, and how the system interacts w ith its surroundings.Training and testing phases have been incorporated into this architecture.Train the image datasets d uring the training phase, then use the convolutional neural network algorithm to extract the features.Next comes the test ing phase, when the user can either input or take the photograph.Utilising the CNN technique, extract the features next.I n order to identify the currency and offer voice alerts about it, categorise the image one last time.
and the notes' denominations as well.

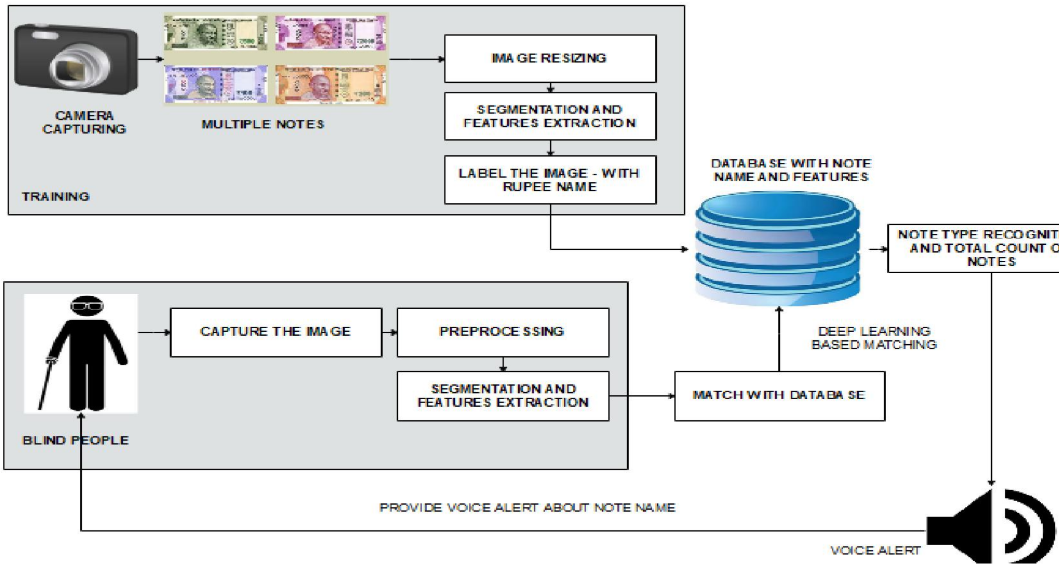


Figure 6. Architecture of proposed Model

V. METHODLOGY

IMAGE ACQUISITION:

In this module, user can input the currency note. Input may be in the form of image or camera capturing. The development of this device is based on a webcam integrated with Raspberry Pi microcontroller and a speaker for sound output. The realtime bank notes are captured and processed through different image processing techniques like edge detection, segmentation, and feature extraction and classification[9].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

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 3, May 2023

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.

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.

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 We have trained the dataset which help to get better accuracy with better sets of data and with the help of testing we how accurate our system we achieve and understand we failed to train our data.[10]The convolutional layers use filters to scan the input images and extract features at different scales, while the pooling layers downsample 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 thefeatures 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

CAMERA CAPTURING:

Blind people can be difficult to recognize the bank notes. In this module, blind people can be capturing the image through camera. There are various ways to obtain image such as with the help of camera or scanner. Acquired image should keep all the features.[11]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 note is provided as the input to the system which undergoes certain pre-processing steps to extract the ROI (Region of interest) from the note. based on ROI, firstly we find the origin of the currency and then secondly denomination based on certain features like dimension, pigment, text clipping on the note which we found in ROI.[12]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.

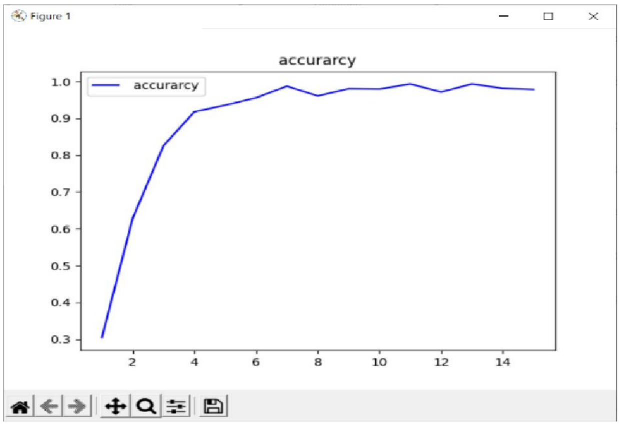
NOTE CLASSIFICATION:

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. In today's modern world many devices use Deep learning language such as Convolution neural network. Most of the industries are now shift from machine language to Deep learning language to gather for the fast-growing rate of technologies around the globe.[13]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.

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.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 3, May 2023



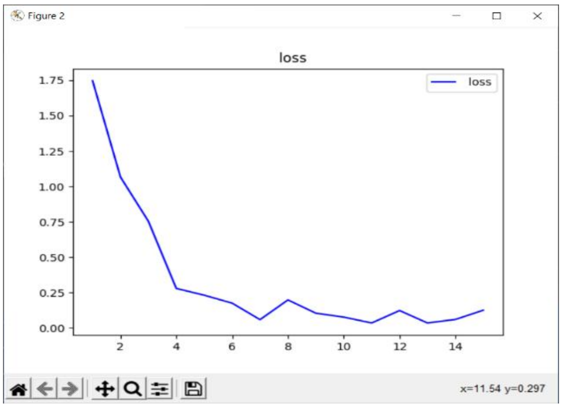


Figure 7. Accuracy and loss graph **Figure8. Accuracy and loss graph**

VI. RESULT AND DISCUSSION

In this project we used build the Indian currency recognition for visually impairment people using deep learning algorithm in we used in CNN algorithm to recognition the Indian currency Rupees for visually impairment people . For a normal person, recognition of currency notes is an easy task but this is not the case for a visually impaired person. A visually impaired person is one who has partial visual impairment or someone who is completely blind. They face a lot of difficulties in day-to-day activities including monetary trans- actions. They have difficulty in recognizing the paper currencies due to similarity of paper texture and size between different categories of currency notes. Institutions like banks can afford expensive hardware to resolve this issue of currency recognition but for common people especially the visually impaired people cannot use this expensive hardware. The aim of this project is to help such people and provide them with a cost-effective solution. The idea of a currency recognition software is proposed in this project which will help in distinguishing different currency notes. [14]CNN picture orders takes a data picture, measure it and brains it under express classes (Eg., Dog, Cat, Tiger, Lion). Workstations accepts a to be picture asshow of pixels and it relies on the picture objective.[15]we will run the program the camera will turn on after turn on the camera we will show the Indian currency Infront of the camera after showing the currency camera will capture the currency and match with the trained dataset if its matched it will say the value of the currency and again you will show the currency it will automatically add and say the value of the Indian currency.

VII. CONCLUSION AND FUTURE ENHANCEMENT

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

VIII. FUTURE ENHANCEMENT

With advancements in hardware technology, it is possible to develop currency recognition systems that can process images in real-time, reducing the processing time and enhancing the user experience. Currency recognition systems can be enhanced to be more robust to variations in image quality, lighting, and perspective, allowing for more accurate recognition in different settings and conditions.

REFERENCES

[1]. R. Jadhav, S. Kalbande, R. Katkar, R. Katta and R. Bharadwaj, "Currency Recognition Using Machine Learning," International Research Journal of Engineering and Technology, vol. 9, no. 1, 2022.

[2]. M. S and A. T, "Counterfeit currency recognition using deep learning: A review," TECHNIUM, vol. 3, no. 7, 2021.

[3]. S. M, "An Intelligent Paper Currency Recognition System," International Conference on communication,Management and Information Technology , vol. 09, no. 06, 2015.

[4]. J. R.C, . Y. S. and D. M.K., "YOLO-v3 based currency detection and recognition system for visually impaired persons.," International Conference on Contemporary Computing and Applications, 2020.

[5]. A. H, A. S, . Z. S and . P. F, "Deep ancient Roman Republican coin classification via feature fusion and attention. Pattern Recognition," Internation Conference on Communication,management and information Technology, 2021.

[6]. X. Y and Y. W.Q, " Fast‑moving coin recognition using deep learning," Multimedia Tools and Applications, 2021.

[7]. P. C.G, B. D.M and R. D, "Fake banknote recognition using deep learning," Applied Sciences, 2021.

[8]. R. P.S and A. T.P, "CNN based framework for identifying the Indian currency denomination for physically challenged people," In IOP Conference Series: Materials Science and Engineering, vol. 992, p. 1, 2020.

[9]. S. Nanda, M. Abbas, N. Momaya and K. A. Mahesh, "Indian Currency Detection for Bilnd people with VGG16," Internation journal of innovative research in technlogy, vol. 8, no. 2, 2021.

[10]. R. Pokala and V. Teja, "Indian Currency Recognition for Blind people," International Research Journal of Engineering and Technlogy, vol. 07, no. 05, 2020.

[11]. S. N.A, F. S.M, E. M.S and G. A.F, " Currency recognition system for visually impaired," International Conference on Information & Communication Technology and Accessibility, 2015.

[12]. S. Bhutada, V. R. K, A. Chevva, S. Kadapala and M. Gella, "Currency Recognition Using Image Processing," International Journal of Scientific Develpment and Research, vol. 5, no. 4, 2020.

[13]. R. Wasi, J. Alick and M. H, "Currency Recognition and Calculation System Using Machine Learning Techniques," Wseas Transactions on Signal Processing, vol. 16, 2020.

[14]. S. Samant, S. Sonawane, R. Thorat, P. S. Bera and K. N.P, "Currency Recognition System For Visually Impaired People," International Journal of Advance Scientific Research and Engineering Trends, vol. 5, no. 3, 2020.

[15]. Y. R, K. G, A. R, M. M and S. M, "Detection Currency Notes For Visually Challenged people Using Machine Learning," Natinal Volatiles & Essential Oils, 2021.