*i*Journals: International Journal of Software & Hardware Research in Engineering (IJSHRE)
ISSN-2347-4890
Volume 11 Issue 10 October 2023

CNN Based Currency Reader For Visually Impaired

Aviraj Singh
Heritage International Experiential School
aviraj1046@gmail.com

Vinay Vishwakarma
On My Own Technology Mumbai-400053, India
vinay.vishwakarma@onmyowntechnology.com

" "*Abstract*- This research aims to develop a prototype that can accurately identify Indian banknotes. Approximately 40 million individuals in India are blind or visually impaired, including 1.6 million children. These individuals face challenges in recognizing and accepting different types of banknotes. To address this, researchers are working on an automated banknote recognition device that can be transformed into a vision-based system. The main objective is to investigate the impact of area and orientation on machine learning and deep learning outcomes specifically for the Indian currency. The goal is to provide visually impaired individuals with user- friendly gadgets that automate the task of identifying Indian banknotes.

Keywords*: *Deep Learning, Image Recognition, Computer Vision, Feature Extraction, Machine Learning, Currency Recognition

I. INTRODUCTION

Modern automation systems in the real world require the implementation of currency recognition systems due to their diverse range of potential applications. These applications include banknote counting machines, money exchange machines, electronic banking systems, currency monitoring systems, and assistance for blind individuals. The ability to recognize currency holds significant importance for blind and visually impaired individuals, as they often struggle to differentiate between different denominations accurately. This vulnerability makes them susceptible to being deceived or cheated by others. Thus, there is an urgent and compelling need to develop a system that can easily and reliably recognize the value of currencies. According to estimates from the World Health Organization, there are approximately 285 million visually impaired people worldwide, with 39 million of them being blind and the remaining having low vision. This staggering number underscores the critical need for automatic currency recognition systems. These systems aim to assist visually challenged individuals by enabling them to distinguish between various types of Indian currencies through the implementation of image processing techniques. This research paper is to investigate and analyses different techniques for recognizing Indian rupee banknotes. By leveraging image processing methodologies, we aim to extract distinct and unique features present on Indian currency notes. Subsequently, specific algorithms will be developed to detect each of these distinct features. This comprehensive approach will contribute to the development of an efficient and accurate currency recognition system. The successful implementation of this proposed work will empower visually impaired individuals to independently identify and differentiate between different types of Indian currencies during their monetary transactions. This newfound ability will significantly enhance their daily lives, allowing them to navigate financial interactions with confidence and self-reliance. In summary, modern automation systems necessitate the integration of currency recognition capabilities due to their wide- ranging applications. Blind and visually impaired individuals face significant challenges in accurately discerning between currencies, making them susceptible to potential exploitation. The present research aims to address this issue by studying and developing automatic currency recognition systems. Specifically, we focus on differentiating between various types of Indian currencies through the utilization of image-processing techniques. By extracting distinct features and employing specialized algorithms, we strive to enable visually impaired individuals to independently recognize different Indian currency denominations during their financial transactions. The present work aims to promote financial reliance among the visually challenged community.

II. LITERATURE REVIEW Hassanpour et al. [1] present a novel paper currency recognition technique method that utilizes size, colour, and texture characteristics. This method successfully recognises currencies from various countries by comparing the computed colour abundance using image histograms with a reference currency and employing the Markov chain for texture modelling. Neural-based techniques used in a banknote machine for recognizing and verifying paper currencies from different countries developed by Frosini et al. [2] Low-cost optoelectronic devices capture refracted light signals, while multilayer perceptrons perform classification and verification. An external controlling algorithm ensures real-time implementation on a microcontroller-basedplatform. Notably, the use of inexpensive sensors yields promising experimental results. Paper currency recognition is crucial in various applications such as banking and automated systems. Zhang et al. [3] propose a method for extracting accurate monetary characteristic vectors from Renmingbi (RMB) currency images. After conducting an extensive review of the existing literature on currency identification, a comprehensive overview of currency recognition is presented by Zhang et al. [4]. Their contributions encompass a consolidation of deep learning methodologies such as CNN, SSD, and MLP, as well as provides a concise outline of potential future avenues for research in this domain. Vedasamhitha et al. [5] carried out a CIA survey that reveals the existence of over 180 currencies worldwide, each with unique attributes in terms of size, colour, and texture. Given the increasing international trade, banks require efficient automated systems to accurately recognize various currency notes, as expecting human tellers to do so individually is impractical. Thus, the need for an efficient automated system that helps in recognizing notes is pivotal for the future. Linear grayscale transformation to reduce background noise emphasizes edge information and performs sorting recognition using a three-layer backpropagation neural network. Single Shot MultiBox Detector (SSD) model based on deep learning as the framework presented by Zhang and Yan [6]. Convolutional Neural Network (CNN) model to extract paper currency features, both front and back denominations can be accurately recognized. The main contribution lies in achieving an average currency recognition accuracy of 96.6% using the CNN and SSD models.

Deep learning specifically in Convolutional Neural Networks (CNN) is utilized due to its effectiveness in computer vision applications. Transfer Learning is employed to overcome data limitations by leveraging pre-existing knowledge from one model to another. The proposed system aims to address the challenges faced by visually impaired individuals in currency recognition in India presented by Saini et al. [7]. Swami et al. [8] developed an optimized model for accurately recognizing Indian paper currencies using a Deep Learning approach with CNN models. This proposed strategy includes training a DL model using Keras and hosting a Flask-based web app on Heroku. These results demonstrate the effectiveness of the algorithm for visually impaired individuals in differentiating various currency denominations.

III. METHODOLOGY

This project is based on an image processing technique. This project aims to recognize currency notes according to their classifications. TFLite models are important aspects of the projects because these tools provide the classified model for the project. CNN classification algorithms are also used in the classification process. The process involves capturing an Indian currency note and converting the captured image into text format. Subsequently, the recognized text is converted into voice format.

Currency recognition has been an area of extensive research in recent years, with various approaches and machine-learning models used to classify currencies based on their special features. Each currency worldwide possesses unique characteristics that aid in its identification. Indian currencies, for instance, possess specific security features important for accurate classification recognition. These features include dominant colour, making it evident that grayscale models for currency recognition may overlook an important classification aspect, potentially affecting accuracy. Another notable aspect is the identification marks found on Indian currency notes, where specific geometric symbols correspond to different classifications.

Fig. 1 Characteristic of Notes

A. The initial step involves dividing the dataset into training and testing sets. Subsequently, a CNN classification method is used to create a classified model, followed by the training process." "*Currency recognition using CNN*

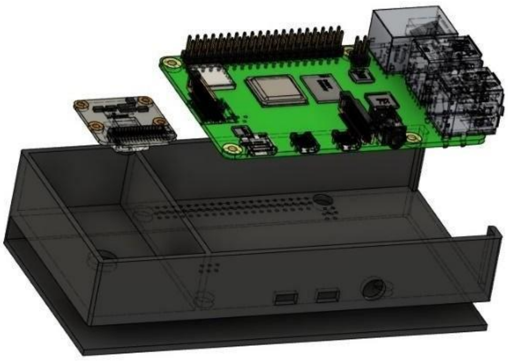
a). Dataset Collection and Cleaning: Collecting samples for the dataset is a significant task in any

ISSN-2347-4890
Volume 11 Issue 10 October 2023

project, as the dataset plays an important role in finding the output of the classification model. Before using the dataset in the classification model, it is important to clean the data to improve the model's image recognition abilities. The present research collected around 1529 images belonging to 3 classes and performed cleaning to improve the classification model. The most effective approach involved removing images with background colours that could prevent the model's performance. Thus, image cleaning emerged as an important step in the overall process.

(a) (b) (c)

Fig. 2 Various types of notes



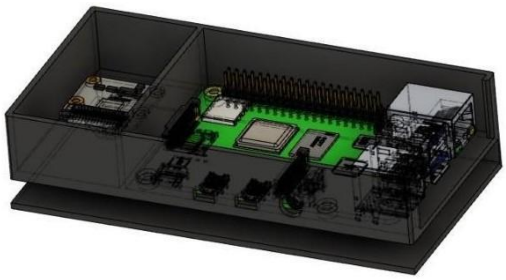


Fig. 3 Unassembled 3-D design of the currency reader

Fig. 4 Assemble 3-D design of the currency reader TABLE I VARIOUS CURRENCY TYPES AND THE COUNT OF CURRENCY FOR EACH TYPE

Type	Currency (Rs)	Number of counts
a	100	502
b	200	545
c	500	482

For model development, 80% of the images are used for training and 20% for validation purposes.

B. Standardize data

The RGB(Red, Green, Blue) channel values vary in the range of [0, 255]. This is not ideal for a neural network; in general input values should be small. However, standardized values vary in the range [0, 1] for using Rescaling layers.

C. Configure Dataset for Performance Considered buffered to generate data from the disk without having I/O become blocked. These are two important methods used during loading data:

Dataset.Cache keeps the images in memory after they're loaded off the disk during the first epoch. This will ensure that the dataset does not become a bottleneck during the training of the present model. Dataset.prefetch overlaps data preprocessing and model execution while training.

D. Data Augmentation

Overfitting occurs due to a small number of training examples. Data augmentation takes the approach of generating additional training data from existing examples using augmenting them using random transformations that generate believable-looking images. This helps to expose the model to more aspects of the data and generalize better.

Fig. 5 Data augmentation

To implement data augmentation using Random Flip, Random Rotation and Random Zoom used for Keras preprocessing layers:

IV. USED MODELS

A. Tensor Flow

TensorFlow is a widely used library that creates and trains machine learning models. It provides a range of functionalities to facilitate the implementation of Convolutional Neural Network Models, including operations such as Convolution, ReLU activation, Pooling, and Flattening.

B. TFLite

TFLite also referred to as TensorFlow Lite, is a toolset that enables the execution of machine learning models on various devices. It provides broad language support and delivers an exceptional performance with TFLite, tasks like image and audio classification, NLP text classification, pose estimation and object detection. The use of Flat Buffers ensures efficiency by optimizing the representation of TensorFlow Lite models, resulting in smaller code sizes and improved performance for speedy inference. TensorFlow Lite models incorporate metadata, containing both human-

“ “readable model descriptions and machine-readable data, which prove valuable for image classification.

V. MODEL BUILDING

A. Build CNN model

Every image is composed of a grid-like structure called a 2D matrix, consisting of pixels with varying RGB colour values. Image processing involves three fundamental steps: 1) importing images using suitable tools, 2) preprocessing and analyzing images, and 3) generating analyzed output.
In the present study, Tensor Flow was for image classification, using images with dimensions of 640x480.

The concept of Convolutional Neural Networks (CNN) recognizes that not all pixels are necessary for identifying image features or performing classification.
The image classification process encompasses several steps, including dataset preparation, convolution, ReLU layer application, pooling, flattening, establishing neural connections, and converting the generated model into the TFLite format.

B. Convolution

Convolution involves integrating two functions to observe how one function influences another.

C. ReLU layer

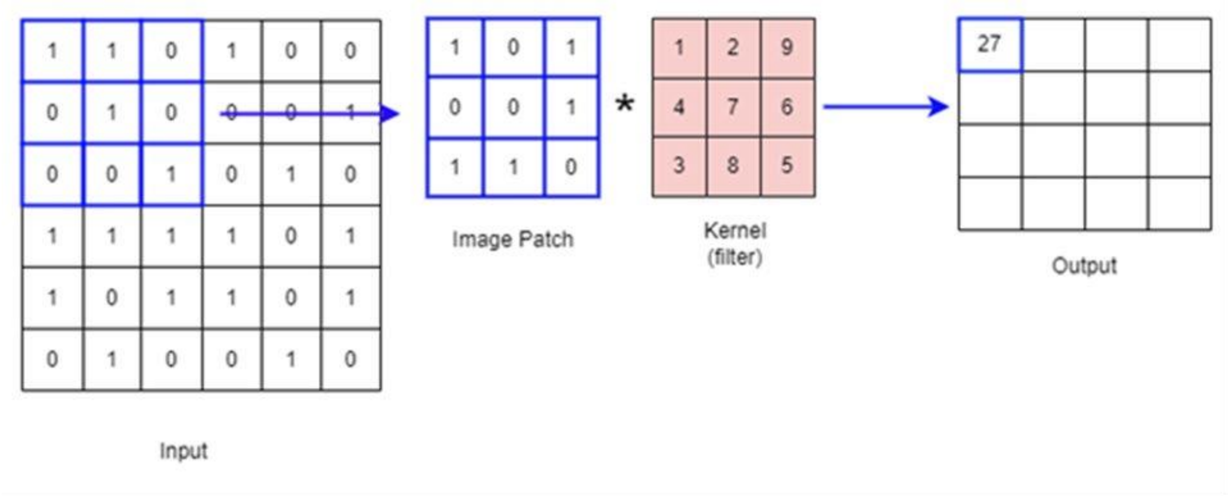


Fig. 6 Convolution architecture

that sets values below zero to a uniform value or" "The ReLU layer is employed to introduce nonlinearity into the image or CNN, acting as a filter flattens them.

D. Pooling

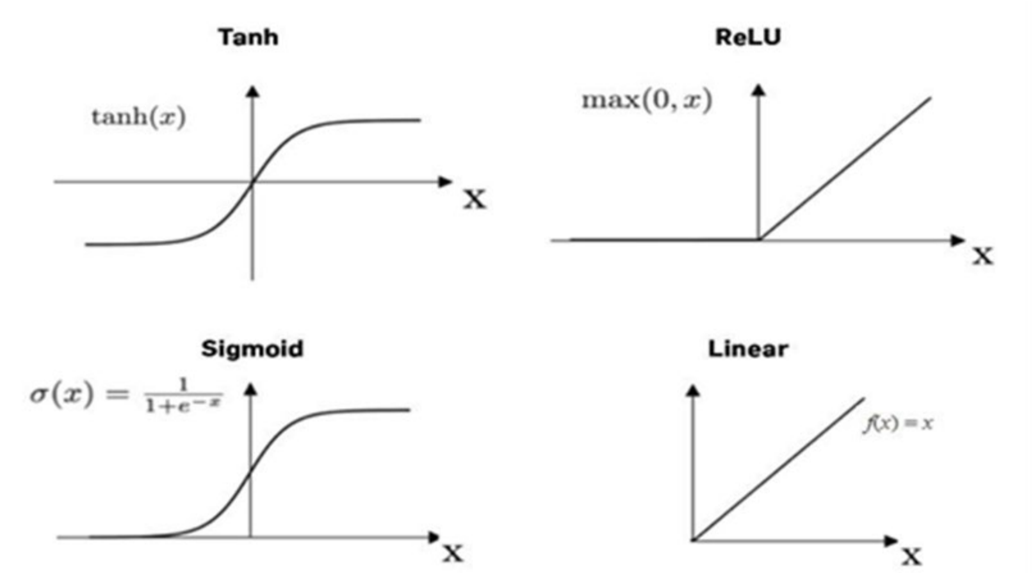


Fig. 7 ReLU Activation Function

Pooling plays an important role in orientation correction for currency notes. It ensures that the neural network recognizes rotated, distorted, or mean or max pooling, ensures spatial invariance, meaning that the network disregards variations in features due to rotation or slight differences.

E. Flattening

Fig. 8 zax Pool

*a). Compile the model" "*Flattening converts the pooled feature map into a linear matrix or a single long column. This matrix serves as input for a Neural Network.

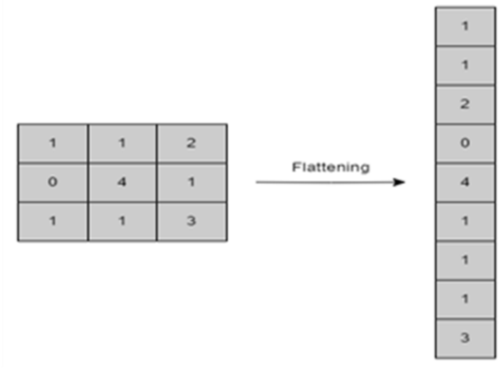


Fig. 9 Flattening

F. Full Connection

In the Full Connection step, the Neural Network is executed, and Backpropagation and Gradient Descent algorithms enable the construction of the entire Neural Network architecture. The model compilation process takes place after constructing the model statements and before commencing training. Its purpose is to validate the syntax and structure of the model, as well as to specify the loss function, optimizer (or learning rate), and metrics to be used. While a compiled model is required for training, it is not mandatory for making predictions. In our scenario, we have chosen to utilize Sparse Categorical Crossentropy as the loss function, Adam as the optimizer, and accuracy as the metric.

b). Train the model

The training process involves iterating over the training data in batches and inputting it into the CNN model. During the forward pass, the model computes predictions, and during the backward pass, gradients are calculated for each parameter. The optimizer uses these gradients to update the model's weights, reducing the loss. In this model, a total of 1224 images were classified, and each image was evaluated based on its accuracy in matching the denomination. Multiple classes were created, each representing a different currency value. The model achieved a validation accuracy of approximately 87%." "

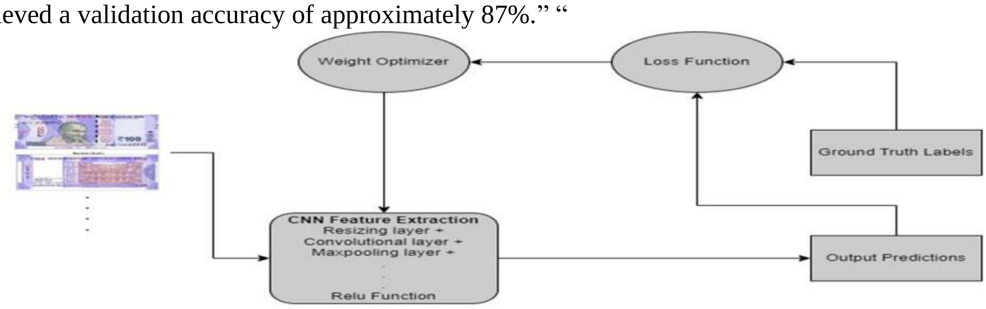


Fig. 10 A schematic representation of a convolutional neural network (CNN) training process" "

```
epochs = 10
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

```
Epoch 1/10
77/77 [==============================] - 14s 150ms/step - loss: 1.7243 - accuracy: 0.5417 - val_loss: 0.6614 - val_accuracy: 0.7607
Epoch 2/10
77/77 [==============================] - 11s 147ms/step - loss: 0.6693 - accuracy: 0.7320 - val_loss: 0.5955 - val_accuracy: 0.7475
Epoch 3/10
77/77 [==============================] - 11s 149ms/step - loss: 0.5752 - accuracy: 0.7614 - val_loss: 0.9541 - val_accuracy: 0.6361
Epoch 4/10
77/77 [==============================] - 12s 150ms/step - loss: 0.5256 - accuracy: 0.7974 - val_loss: 0.6956 - val_accuracy: 0.7082
Epoch 5/10
77/77 [==============================] - 12s 149ms/step - loss: 0.4944 - accuracy: 0.8162 - val_loss: 0.5055 - val_accuracy: 0.8230
Epoch 6/10
77/77 [==============================] - 11s 149ms/step - loss: 0.3896 - accuracy: 0.8570 - val_loss: 0.4190 - val_accuracy: 0.8426
Epoch 7/10
77/77 [==============================] - 11s 148ms/step - loss: 0.3534 - accuracy: 0.8717 - val_loss: 0.3875 - val_accuracy: 0.8754
Epoch 8/10
77/77 [==============================] - 11s 148ms/step - loss: 0.3022 - accuracy: 0.8832 - val_loss: 0.3867 - val_accuracy: 0.8754
Epoch 9/10
77/77 [==============================] - 11s 146ms/step - loss: 0.3380 - accuracy: 0.8775 - val_loss: 0.4363 - val_accuracy: 0.8295
Epoch 10/10
77/77 [==============================] - 11s 144ms/step - loss: 0.2789 - accuracy: 0.8979 - val_loss: 0.2776 - val_accuracy: 0.8820
```

Fig. 11 Training and validation accuracy in the training process

VI. *RESULT*

A. *Training and validation accuracy per epoch*

To improve accuracy in machine learning models, it is common practice to adjust the loss factor during training. This involves training the model for multiple epochs and monitoring the accuracy of a dataset. By doing so, one can observe the accuracy trends over time and adjust accordingly.

Fig. 12 Graph of training and validation accuracy in the training process

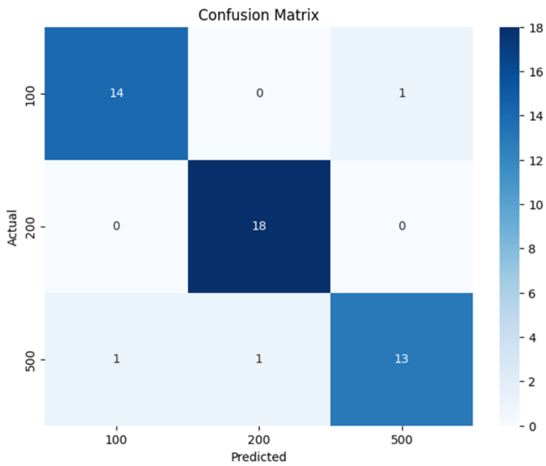


Fig. 12 Graph of training and validation loss in the training process

B. *Confusion matrix for testing data*

In Figure 11, the Confusion Matrix displays the results for all three classes. The x-axis represents the true class labels, while the y-axis represents the predicted class labels. The diagonal elements correspond to correct classifications, while the remaining entries indicate misclassifications. The confusion matrix is based on a dataset consisting of 15 samples from class 100, 18 samples from class 200, and 15 samples from class 500.

Class	**Accuracy (%)**	**Samples**
100	93.33	15
200	100	18
500	86.66	15

C. *Testing Accuracy Per Class*

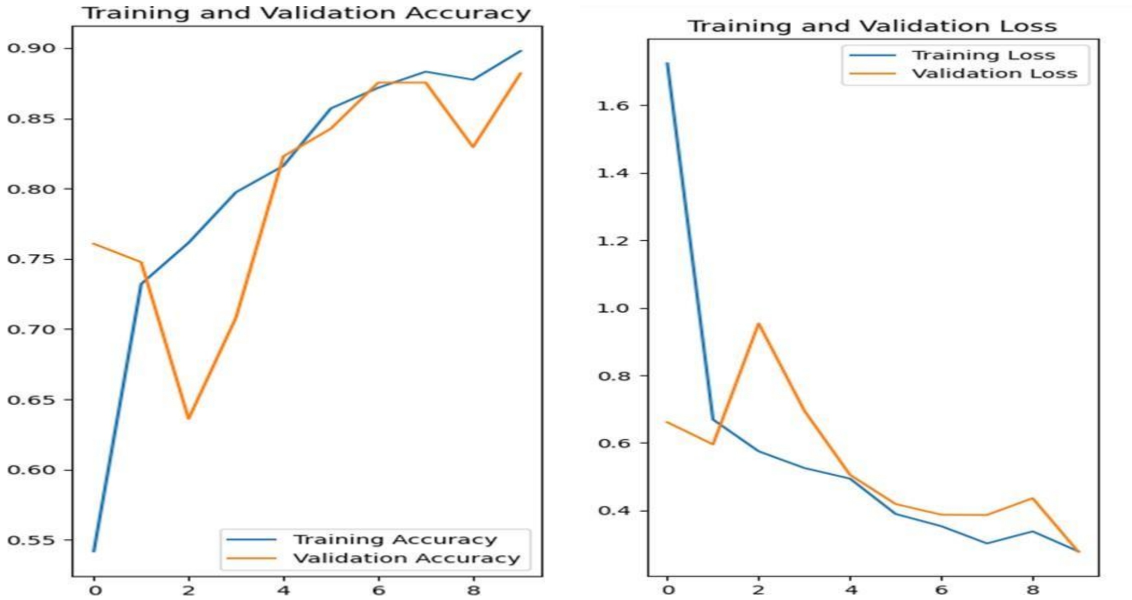


Fig. 13 Actual and Predicted Confusion Matrix

REFERENCES

[1]. Hassanpour, Hamid, A. Yaseri, and G. Ardeshiri. "Feature extraction for paper currency recognition." In 2007 9th International Symposium on Signal Processing and Its Applications, pp. 1-4. IEEE, 2007.

[2]. Frosini, Angelo, Marco Gori, and Paolo Priami. "A neural network-based model for paper currency recognition and verification." IEEE transactions on neural networks 7, no. 6 (1996): 1482-1490.

[3]. Zhang, Er-Hu, Bo Jiang, Jing-Hong Duan, and Zheng- Zhong Bian. "Research on paper currency recognition by neural networks." In Proceedings of the 2003 international conference on machine learning and cybernetics (IEEE Cat. No. 03EX693), vol. 4, pp. 2193-2197. IEEE, 2003.

[4]. Zhang, Qian, Wei Qi Yan, and Mohan Kankanhalli. "Overview of currency recognition using deep learning." Journal of Banking and Financial Technology 3 (2019): 59-69.

[5]. Abburu, Vedasamhitha, Saumya Gupta, S. R. Rimitha, Manjunath Mulimani, and Shashidhar G. Koolagudi. "Currency recognition system using image processing." In 2017 Tenth International Conference on Contemporary Computing (IC3), pp. 1-6. IEEE, 2017.

[6]. Zhang, Qian, and Wei Qi Yan. "Currency detection and recognition based on deep learning." In 2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), pp. 1-6. IEEE, 2018.

[7]. Bhavsar, Kushal, Keyurbhai Jani, and Rakeshkumar Vanzara. "Indian currency recognition from live video using deep learning." In Computing Science, Communication and Security: First International Conference, COMS2 2020, Gujarat, India, March 26– 27, 2020, Revised Selected Papers 1, pp. 70-81. Springer Singapore, 2020.

[8]. Trinh, Hung-Cuong, Hoang-Thanh Vo, Van-Huy Pham, Bhagawan Nath, and Van-Dung Hoang. "Currency recognition based on deep feature selection and classification." In Intelligent Information and Database Systems: 12th Asian Conference, ACIIDS 2020, Phuket, Thailand, March 23–26, 2020, Proceedings 12, pp. 273-281. Springer Singapore, 2020.

[9]. Saini, Poonam, Ankit Goyal, Bishwash Pokhrel, Jaspreet Singh, and Neetish Kumar. "Indian Currency Recognition: A Lightweight Transfer Learning Approach for Visually Impaired." In 2022 Seventh International Conference on Parallel, Distributed and Grid Computing (PDGC), pp. 248-252. IEEE, 2022.

[10]. Saini, Poonam, Ankit Goyal, Bishwash Pokhrel, Jaspreet Singh, and Neetish Kumar. "Indian Currency Recognition: A Lightweight Transfer Learning Approach for Visually Impaired." In 2022 Seventh International Conference on Parallel, Distributed and Grid Computing (PDGC), pp. 248-252. IEEE, 2022.

[11]. Swami, Rohit, Smiti Khurana, Shubham Singh, Sanjeev Thakur, and Pavan Kumar Reddy Sajjala. "Indian Currency Classification Using Deep Learning Techniques." In 2022 12th International Conference on Cloud Computing, Data Science & Engineering (Confluence), pp. 567-572. IEEE, 2022.