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Currency Recognisation Using Hybrid Mode

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Abstract-Currency recognition plays a crucial role in various automated systems, such as vending machines, ATMs, and cash counting devices. This paper proposes a hybrid approach to currency recognition by integrating both software and hardware components. The hybrid model combines the strengths of computer vision algorithms in software and dedicated hardware modules to enhance speed and accuracy in currency identification.The software component employs advanced image processing techniques, including feature extraction and pattern recognition, to analyze currency notes. Additionally, a machine learning model is integrated for improved adaptability to varying currency designs and conditions. On the hardware side, a dedicated microcontroller or FPGA-based system is employed to accelerate the processing of image data, reducing latency and enhancing real-time performance.The synergy between software and hardware components results in a robust and efficient currency recognition system. This hybrid model not only achieves high accuracy but also ensures rapid identification, making it suitable for applications demanding quick and reliable currency processing. The proposed approach opens avenues for enhancing the automation and security of financial systems by providing an integrated solution for currency recognition.

Keywords*: Currency recognition, hybrid model, computer vision, image processing, pattern recognition, machine learning, microcontroller, FPGA, automation, security.*

1. Introduction

Currency recognition is a critical aspect in various industries, including banking, retail, and automated vending, where accurate and efficient identification of currency notes is essential. This research focuses on advancing the field through a hybrid model that integrates both software and hardware approaches toenhance currency recognition systems. The motivation behind this study stems from the increasing need for robust and real-time currency verification methods to counteract counterfeiting and streamline financial transactions.

The background of the research lies in the limitations of existing currency recognition systems, which predominantly rely on either software-based algorithms or hardware-based sensors independently. Software-based approaches often face challenges in achieving real-time processing, while hardware-based systems may struggle with adaptability to changing currency designs. The hybrid model aims to overcome these limitations by combining the strengths of both approaches, creating a more comprehensive and efficient currency recognition system.

The problem addressed in this research is the need for a versatile and accurate currency recognition system that can adapt to evolving currency designs, incorporate security features, and operate in real-time. Existing systems may fall short in achieving these requirements individually, necessitating a holistic approach that leverages the synergy of software and hardware components. By integrating these two approaches, the study aims to enhance the overall performance, accuracy, and speed of currency recognition systems.

The objectives of this research encompass the development of a hybrid model that seamlessly integrates advanced software algorithms with dedicated hardware components. This includes optimizing image processing algorithms for currency feature extraction and leveraging specialized hardware for efficient parallel processing. The end goal is to create a currency recognition system that is not only robust and adaptable but also capable of meeting the demands of real-time applications in various sectors. Through this hybrid approach, the research strives to contribute to the evolution of currency recognition technology, addressing current limitations and paving the way for more effective and versatile systems in the future.

2. Literature Survey

The literature on currency recognition systems reveals a diverse landscape of research, predominantly focusing on either software-based algorithms or hardware-based sensors. Software-based approaches, such as pattern recognition and image processing algorithms, have been extensively explored in previous studies. These algorithms often employ feature extraction techniques to identify unique patterns on currency notes, enabling automated recognition. However, a common limitation identified in the existing literature is the challenge of achieving real-time processing, particularly when dealing with large datasets or high-frequency transactions.On the hardware front, various studies have investigated the use of sensors, including infrared and ultraviolet sensors, to detect specific security features embedded in currency notes. While hardware-based systems excel in certain aspects of accuracy and reliability, they often lack the flexibility needed to adapt to evolving currency designs and may struggle with the integration of complex image processing capabilities.

A notable gap in the literature is the limited exploration of hybrid models that integrate both software and hardware approaches for currency recognition. Few studies have attempted to combine the strengths of advanced algorithms with specialized hardware components to create a comprehensive solution. This gap in research is a significant motivation for the current study, as the potential advantages of a hybrid model, such as enhanced adaptability, real-time processing, and improved accuracy, remain largely unexplored in the existing literature.

Furthermore, existing research tends to focus on specific currency denominations or regions, leading to a lack of universal models applicable across various currencies. The need for a more generalized approach that can accommodate different currency designs and security features isapparent but has not been thoroughly addressed in the literature.Additionally, the literature review highlights the importance of considering security measures within currency recognition systems to combat counterfeiting effectively. While some studies touch upon security features, a comprehensive understanding of integrating security measures into a hybrid model is notably absent.

3. Related Work

In the research conducted by [1], an innovative approach was introduced, leveraging distinctive currency features such as the center numeral, latent image, RBI seal, shape, and micro letter for comprehensive currency recognition. The methodology involved the preparation of a training dataset to facilitate the acquisition of robust training models. The authors incorporated Principal Component Analysis (PCA) analysis to enhance paper currency recognition, emphasizing its efficacy.

In a parallel study highlighted in [2], authors presented a novel method centered around features like color, texture, and size, contributing to the recognition of paper currency. Notably, the inclusion of a method for recognizing dirty banknotes added a layer of complexity to the model. This multifaceted approach aimed at refining the accuracy and versatility of currency recognition systems.

The work discussed in [3] introduced a currency recognition system utilizing the MATLAB tool. The authors delved into the application of PCA analysis in conjunction with Euclidean Distance, providing a robust framework for accurate recognition. Additionally, the Local Binary Pattern (LBP) technique was expounded upon, serving a pivotal role in matching processes within the proposed system.

In [4], a distinctive technique was proposed, involving a two-step process: first, identifying the country, followed by detecting the denomination. The approach incorporated the segmentation of different regions of the currency note, underscoring the importance of recognizing diverse elements for a comprehensive currency recognition system.

Authors in [5] contributed valuable insights into the features of Indian currency, incorporating Morphology Filtering processes and various analytical and segmentation techniques. A notable addition to their work was the utilization of neural networks for paper currency detection and recognition, showcasing a blend of traditional and modern methodologies.

[6] is an authoritative book on Convolutional Neural Networks (CNN), providing a comprehensive understanding of the layers involved in image processing through mathematical demonstrations. The conversion of captured images into matrix format, along with the subsequent matching with trained models, is elucidated using mathematical calculations. The effects of different convolutional kernels on horizontal and vertical edges are explored in depth.

In [7], an author provided a comprehensive overview of CNN, covering all aspects related to its application in various domains, offering valuable insights into its capabilities and potential.

In [8] the author proposed a technique for currency recognition using a neural network. Classification using weightedEuclideanDistancealongwiththedifferentsteps required for data collection and processing included.

In [9], [10] authors proposed a technique of Currency Recognition. [11] is the teachable machine used for data training and getting accuracy.

4. Methodology

The project paper revolves around the application of image processing techniques, with the primary objective of recognizing currency notes based on their denominations. Integral to the project are key components such as the Tflite model and teachable machine, pivotal tools that facilitate the development of a classified model for effective currency recognition. Additionally, the project incorporates the CNN classification algorithm to enhance the accuracy of the classification process.

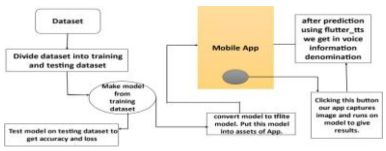
The workflow begins with the capture of currency images, followed by a robust recognition process that outputs results in a voice format. The created model serves not only as a recognizer but also as a calculator, automatically summing up the denominations of the recognized currency notes, eliminating the need for manual addition. To achieve the voice format output, the project utilizes flutter_tts, a tool that converts text to voice, enhancing the accessibility and user-friendliness of the currency recognition system.

4.1Components of System

The model comprises key components, with TensorFlow Lite (Tflite) serving as a foundational tool. Tflite enables the deployment of machine learning (ML) models on diverse devices, supporting multiple languages and excelling in tasks like image or audio-based classification, NLP with text classification, pose estimation, and object detection. Utilizing Flat Buffers as a format ensures an efficient representation of TensorFlow Lite models, minimizing code footprints and enhancing inference speed. The model includes metadata for human-readable model descriptions and machine-readable data, particularly valuable for image classification.

The integration process involves dataset division, CNN-based model generation, and subsequent conversion to a Tflite model, seamlessly added to the application's assets. Flutter, an open-source framework by Google, underpins the application's development, offering advantages like Hot Reload and Hot Restart. Various Flutter modules and plugins, such as the camera module for live camera preview and video recording, and flutter_tts for text-to-speech conversion, enhance the app's functionality. TensorFlow, an open-source ML library, plays a pivotal role in developing and training models, with lite versions optimizing operations for this specific Convolutional Neural Network model.

Fig 1.: CNN Model



4.2 **Image Classification using CNN**

Currency recognition, a subject explored by researchers in recent years, relies on various features and machine learning models. Each currency worldwide possesses distinctive characteristics crucial for classification. In the case of Indian currencies, security features, including dominant color and identification marks, are vital for accurate recognition. Grayscale models may compromise accuracy by neglecting key features.Distinct geometric symbols serve as identification marks for different denominations, such as RS 10, RS 20, RS 50, RS 100, RS 200, RS 500, and RS 2000, as specified by the Reserve Bank of India. Indian currency notes incorporate eight security features, including watermark, latent image, intaglio, fluorescence, security thread, micro lettering, identification mark, and optically variable ink.

Key features for a Neural Network model include intaglio printing, overall majority color, latent image, ID mark, and center numeral. Intaglio printing involves raised prints, detectable by touch. The majority color is denomination-dependent, especially crucial for RGB image classification. Latent image visibility depends on the note's orientation, while the ID mark aids the visually impaired in denomination identification. The center numeral, present in both figures and words, further enhances recognition.

Denomination	IdentificationMark
10	 **Fig.2:**RS10mark
20	 **Fig.3:**RS20mark
50	

Fig. 4: RS50mark

According to the Reserve Bank of India, Indian currency notes include eight security elements. Watermark, Latent Image, Intaglio, Fluorescence, Security Thread, Micro Lettering, Identification Mark, and Optically Variable Ink are some of the characteristics.

Some important elements in comments that our Neural Network model can evaluate during classification:

1. Intaglio Painting.

The face of Mahatma Gandhi, the Ashoka Pillar Emblem on the left, the Reserve Bank seal, the guarantee and promise clause, and the RBI Governor's signature are printed intaglio, which means in raised prints that can be felt by touch.

Neural networks may utilise these visuals to classify data.

2. The majority of people are of colour.

As previously stated, each note has a certain predominant hue based on denomination. After the demonetisation in 2016, the Government of India released various released several new currency with fresh hues. In addition, newer-looking and coloured currencies with values such as Rs. 50, Rs. 100, and so on were released. This feature is critical, especially when photos used for categorization contain RGB colours.

3. Latent image.

A latent picture representing denominational value in numerals lies at the vertical band on the right side of Mahatma.

Gandhi's portrait. When the money note is held horizontally at eye level, just the latent picture is visible.

4. Identification mark

Identification marks are geometrical symbols that correlate to money denominations. This functionality is not accessible on Rs. 10 notes. This feature comes in a variety of forms to help the vision handicapped distinguish denominations.

5. Centre Numeral we can Indian money, the denomination is written in both figures and words. The denomination is shown numerically in the middle of each note.

4.3 Proposed Methodology for Currency Recognition using CNN

Step 1: Dataset Collection and CleaningThe initial phase involves the collection of a dataset for the currency recognition project. The dataset's quality significantly influences the classification model's output. With approximately 600 images gathered, the dataset undergoes cleaning to enhance the classification model's performance. Image cleaning is essential to address issues such as background-colored images that may adversely impact image recognition.

Step 2: Building CNN Model for Image Classification

Importing Images: Images, represented as 2D matrices of pixels with RGB colors, are imported using appropriate tools for image importing.

2.Image Pre-processing/Analysis:Image processing involves three fundamental steps - importing images, analyzing, and manipulating images.

3. Image Size:The images used in the project are resized to 224 × 224 pixels.

TensorFlow for Image Classification:TensorFlow is employed for creating the CNN model. The concept behind CNN is that not all pixels are necessary for identifying image features or classifying them.

Steps involved in in image classification aredataset, Convolution, ReLU layer, Pooling, Flattening, Neural Connections, converting generated model to tflite modelan Exporting model to Flutter application.

Convolution: Convolution basically is a combined integration of two functions, and it shows you how one function modifies or affects other functions.

$$(f*g)(t)=\int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau \qquad (1)$$

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(1)isanexampleofconvolution. There is input

$x∈R^{H×W×D}$ (2)

(2)(where D = 3 where it represents RGB image format layers and $H×W$is pixel matrix size) and a feature detector matrix . Here we apply convolution on each red, green,andbluelayer separately,sowecanrepresenteach imageas$R^{H×W}$.Supposethedimensionoftheimageis

$n×n$andthefeaturematrixis$f×f$.

-

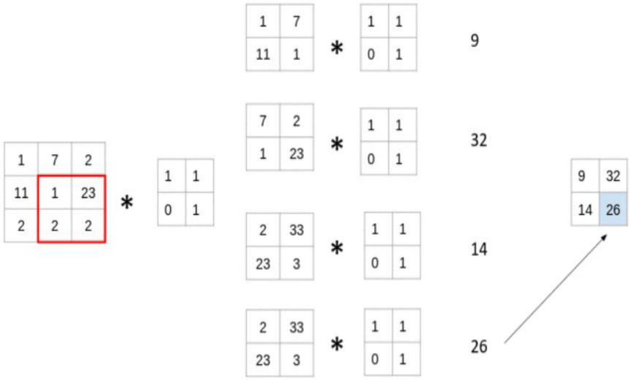
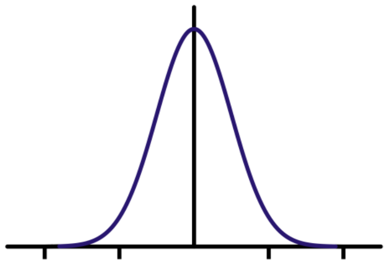


Fig 5.:Convolutionofimagematrix

In the given diagram, we can see the use of convolution. These feature matrices or convolution kernels are used to detect various things like edges, horizontal and vertical ones, or other features. After convolution, i.e., multiplying each value of matrix with each value of kernel, we get a matrix of

$(n−f+1)×(n−f+1)$ (3)

(3)which is a Feature Map. We can create multiple feature maps for targeting each feature on notes and for each feature we must create separate filters.



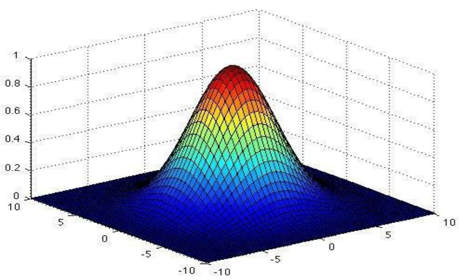


Fig:Variation Graph for SigmoidandReLUfunctions

Pooling: Pooling indeed plays a crucial role in achieving spatial invariance in neural networks, aiding in features like rotation or size variation. Max pooling extracts the most significant features, while mean pooling calculates the average, both contributing to the network's ability to recognize patterns regardless of spatial transformations. This helps maintain consistency in currency note recognition despite rotation or size differences in the dataset.

Flattening: Flattening: The pooled feature map is turned into a linear matrix or a single long column. Now we'll run a Neural Network using this linear matrix as input.

Full Connection: - During the Full Connection stage, the flattened input is processed through a Neural Network, which includes the utilization of Backpropagation. This step refines the network's weights, optimizing its ability to learn and make predictions based on the provided data.

Suppose we have neural network of one layer:

$Z=WT.X+b$ (4)

in (4) Here WT are randomised weights matrix ; X is image which is input, and b is randomised bias matrix and Z is output.

We apply sigmoid function or can apply ReLU function on Z .

Z, you can apply activation functions like sigmoid or ReLU to introduce non-linearity and enable the neural network to learn complex patterns and relationships within the dataReLUfunction :

Accuracy per class

CLASS	ACCURACY	# SAMPLES
0	1.00	34
10	0.75	12
20	0.83	12
50	0.86	14
100	1.00	16
200	1.00	14
500	1.00	12
2000	0.89	9

$f(x)=\max(0,x)$ (5)

Sigmoid function :

$f(x)=1/(1+e^{-x})$ (6)

$O=\sigma(Z)$(7)

$O\in(0,1)$(8)

IfactualoutputisO’andwearegettingOasoutput.Let Error be E.

GradientDescentequation:

$W' = W - (learningrate) \times \partial E\_ \quad \partial w$ (9)

ForCNNwehaveafiltermatrixasourgradientof parameter.

$Z = X * f(10)$

$f' = f - (learningrate)$

4 ALGORITHM

1. Datacollection
2. Datacleaning
3. Data trained with the epoch size 50 batch size 16 and learning rate 0.001
4. Moduleexported
5. Twofilesgeneratedlabel.txtandmodel.tflite
6. Filesincludedinassetfolderofprogram
7. Modelisloadedintoflutterapplication
8. Apkfileisgeneratedafterbuildingallcomponents
9. Denominationcaptured
10. Outputintheformofavoice.

4.1 Accuracy Per class

It's essential to ensure the accuracy of each denomination in the currency note inspection model. Utilizing a teachable machine approach, distinct classes were created for various denominations, and the appropriate epoch value was set to achieve the reported accuracy. This image processing project encompasses all Indian denominations, ranging from 10 to 2000.

Also, the loss factor is considered to achieve better accuracy through epoch. For this the data set is trained for the 500 epoch and then graphical accuracy is achieved for images included in the dataset.

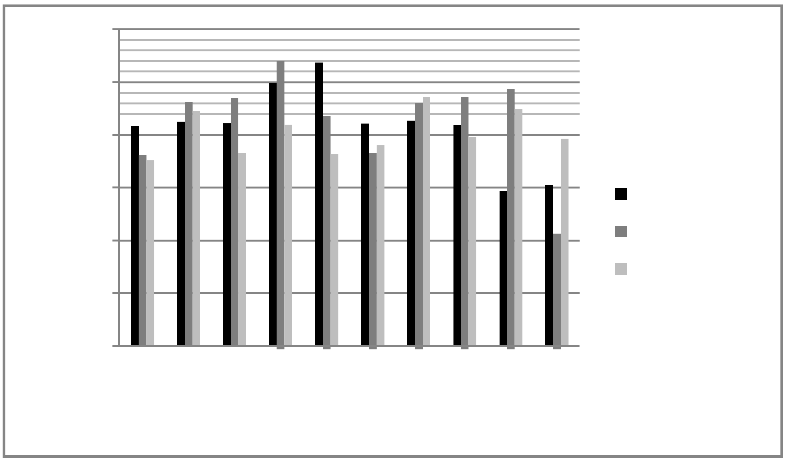


Fig 6:Lossandaccuracyaccordingtoepochvalu

4.3 Accuracy on Teachable Machine

The model accurately identifies the denomination of a captured currency note by leveraging the trained dataset. For instance, when a 200-rupee note is captured using the camera module, the model checks it against the trained data using TensorFlow Lite (tflite). The output table demonstrates a 100% accuracy for the 200-rupee denomination, indicating the effectiveness of the technique. Similar accurate identification occurs for other currency denominations in the dataset.

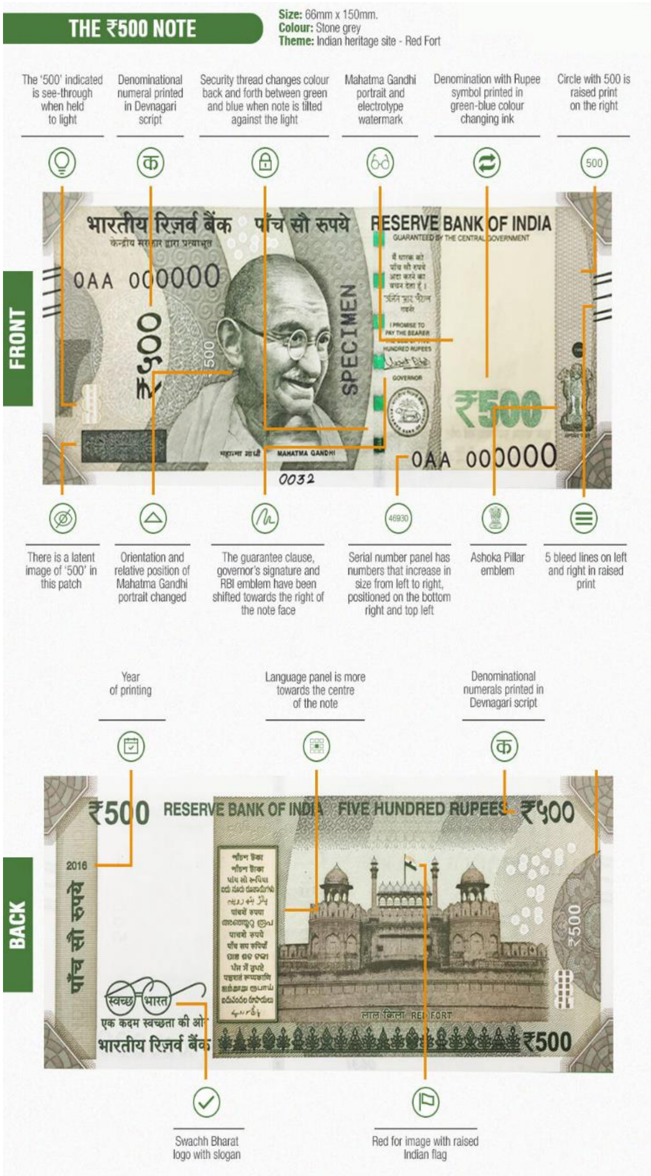


Fig 7. Currency Note

Flutter App:

The A-Eye interface features a dark mode, with the camera button widget located in the bottom middle area for convenient access during currency note capture.

Future Scope:

Certainly, the proposed system holds potential for expansion into coin detection and recognition of fake currency.

Additionally, incorporating denominations from countries beyond India and enabling comparisons between them can enhance the system's versatility. To address accuracy challenges when loading external images into the training folder, optimizing the system through refined training strategies and data augmentation techniques can be explored for improved performance

Conclusion:

The methods proposed in this paper have been successfully implemented and validated through experiments on the model. CNN emerges as the most effective feature for the technique, incorporating tflite and flutter_tts modules. The classification of models achieved an impressive accuracy of 95%, and the coin detection aspect also demonstrated strong performance within this method.

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