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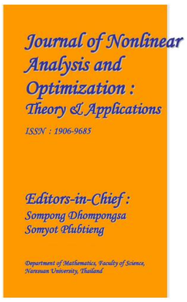

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DENOMINATION DETECTION USING YOLOv5 ALOGORITHM

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ABSTRACT: The goal of deep learning-based denomination recognition is to help people with visual impairments distinguish between different currencies. The proposed methodology can be used to determine the value or denomination of a specific banknote. Convolutional neural networks (CNNs) are trained on a large dataset of banknote images from various categories, and they play an important role in the whole system. The system uses convolutional neural networks (CNNs) to detect the visual characteristics of various cash notes and offer the user with rapid audible feedback. The device uses a camera to capture an image of the banknote and allows users to upload their own photos. The CNN model then analyzes these photos to determine the denomination of cash. This system can detect many currencies concurrently and with excellent accuracy. This system uses algorithms that are specifically developed to detect and extract distinctive and distinct properties from currency notes, such as text, color band, logo, and special symbols or marks for the visually handicapped. Our research seeks to empower people with visual impairments by allowing them to autonomously distinguish between different currencies during financial transactions, so increasing their autonomy in social and financial realms.

Keywords: *CNN, YOLOv5, Denomination, Dataset, Deep learning, ENN, GLCM.*

1.INTRODUCTION

Denomination identification is an important task in fields like banking and security, where quick and accurate money recognition is necessary. Previously, denomination recognition relied on human feature engineering and deep learning algorithms, which were time-consuming and error-prone. Denomination recognition has improved significantly in terms of accuracy and speed as deep learning technology has advanced. Convolutional Neural Networks (CNNs) are deep learning algorithms renowned for their superior performance in image recognition applications. These algorithms can automatically extract features from pictures, eliminating the need for manual feature engineering.

CNNs can identify and classify coin-specific features like as textures, patterns, and symbols. As a result, they are an excellent tool for recognizing different denominations. One of the key advantages of deep learning algorithms is their ability to extract knowledge from large image datasets. As more high-quality image datasets become available, deep learning systems' ability to detect denominations is projected to improve. Given this perspective, implementing a large-scale deep learning effort to detect denominations could be a fantastic way to investigate the possibilities of these algorithms in this specific domain. A project of this magnitude would require the creation and execution of a sophisticated deep learning algorithm capable of reliably recognizing various currencies from photographs. It would also entail testing the algorithm's effectiveness across numerous datasets and possibly investigating additional deep learning structures or approaches to improve accuracy and efficiency. Overall, the field of deep learning-based denomination recognition is fascinating and quickly evolving, having the potential to transform how we recognize and classify different currencies.

2.EXISTING SYSTEM

The existing technology has demonstrated that the texture and color of banknotes may be retrieved and utilized to classify them. This technique identifies using Local Binary Patterns and the RGB color model. This approach has a noticeably low level of accuracy. To extract distinguishing features, we employed the block LBP approach, which is an upgraded version of the Local Binary Patterns (LBP) technique. The classic Local Binary Pattern (LBP) technique serves as the foundation for this approach. This approach works slowly but is incredibly simple to use.

One limitation of existing technology is that it can only recognize individual banknotes and cannot distinguish several currencies inside a single input system. When the cash is rotated and positioned at an angle, the system fails to recognize it due to insufficient feature extraction.

3.LITERATURE SURVEY

Numerous researchers have contributed significantly to the evolution of coin identification systems. Researchers approach the problem of coin and note identification differently because to the characteristics that distinguish them from one another. In this section, we will look at previous research on currency recognition techniques.

The authors, Shamika Desai[1] et al., proposed a method in 2021 that underlines the critical need of counterfeit currency recognition due to the evolving fraudulent strategies and economic ramifications. To address the lack of publicly available detection tools, it proposes a unique strategy that employs Convolutional Neural Networks (CNNs) for feature extraction and Generative Adversarial Networks (GANs) for determining if Indian paper currency is real or fake.Ahmed Y. A. Saeed [4] et al. suggested a method in 2021 that highlights the importance of precise paper cash recognition systems, which are required for automated banking machines and visually impaired persons. It describes a dependable method that employs pre-trained models such as AlexNet, DenseNet121, and ResNet50 in conjunction with deep learning.Using image processing and deep learning techniques, Uttoran Roy Chowdhury [5] et al. presented an automated system for Indian banknote recognition in 2020 that maintains orientation invariance and independence from note sides or faces. Before employing k-NN classification based on color and texture data or feeding photos directly to a Convolutional Neural Network (CNN) for denomination classification, the system preprocesses them to correct rotation.

In 2022, The Author Abilash CS [6] et al. developed an Android mobile application to assist visually challenged people with the problems they face when recognizing currency. The project attempts to improve automated banknote recognition by using image processing techniques and emphasizing color and form characteristics to accurately identify Indian rupee notes. It accomplishes this by investigating the influence of area and orientation on machine learning and deep learning results.

In 2018, Shubham and Shiva Mittal[7] presented a deep learning strategy based on transfer learning to distinguish Indian rupee currency denominations from color pictures. This strategy is ideal for creating portable systems.

Uttoran Roy Chowdary [8] et al. presented an automated technique for Indian banknote recognition in 2020 that ensures orientation invariance and independence from note faces. It uses a Convolutional Neural Network (CNN) for direct classification and a k-NN for feature-based classification to identify denominations.

In 2018, the author Qian Zhang [9] et al. employed CNN feature extraction in conjunction with deep learning—specifically, the SSD model—to correctly recognize banknote denominations on both the front and back sides.

4.PROPOSED SYSTEM

The suggested system uses the YOLOv5 algorithm to identify cash in numerous input photos. After transfer learning training, the model is inferred using test data. The Flask framework and the YOLOv5 model are used to develop a web application. After uploading a snapshot of the note, this program displays audio snippets and on-screen labels for detected currency notes. This would not only benefit those who are blind or visually handicapped, but it will also make it easier for tourists and foreign visitors to India to recognize Indian cash.

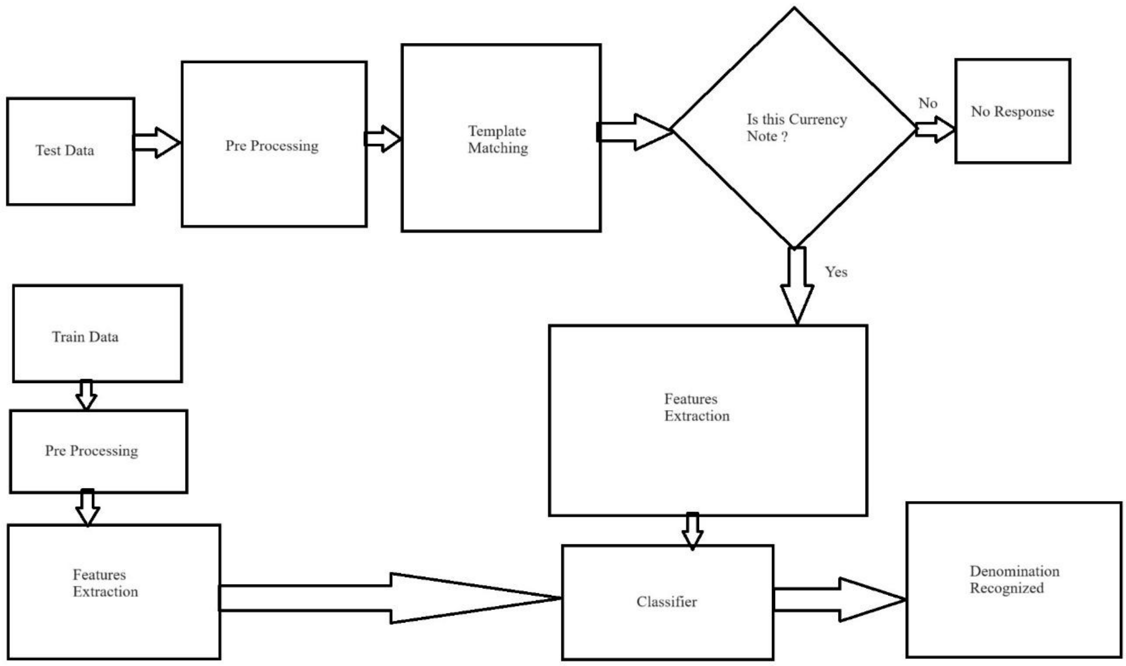

Fig.1.Block Diagram

Currency recognition systems typically consist of several interconnected modules that work together to detect and categorize banknotes. The specific modules may vary depending on the implementation, but the following are a few examples of common modules:

Image acquisition: Using a scanner or camera to capture an image of the cash.

Pre-processing: During this stage, the image is cleaned and preprocessed to remove any interference or distortion. These activities, like altering perspective, decreasing noise, and correcting color, may be required.

Feature extraction: This stage involves extracting relevant elements from the previously studied image that will aid in the identification of the cash. These features include the currency's tactile feel, shape, size, and color, among others.

Classification: At this point, the collected features are fed into a deep learning network that has been trained to recognize various currencies. The classifier makes predictions about the currency based on the provided features.

Audio output generation: The recognized text is converted to audio and delivered via audio using the gtts library.

If f(x,y) and t(x,y) denote the image and the template respectively, then their normalized cross-correlation will be:

$$\frac{1}{n}\sum_{x,y}\frac{1}{\sigma f.\sigma t}f(x,y)t(x,y) \quad (1)$$

Contrast is given by,

$$con = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2 \quad (2)$$

Correlation is given by,

$$cor = \sum_{i,j=0}^{N-1} P_{ij}\frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (3)$$

Energy is given by,

$$eng = \sum_{i,j=0}^{N-1} (P_{ij})^2 \quad (4)$$

Homogenesity is given by,

$$hmg = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \quad (5)$$

Where, Pij = Element ij of normalised symmetrical GLCM

N = Number of gray levels in the image

μ = the GLCM mean

σ 2 = the variance of the intensities of all reference pixels in relationships that contributed to the GLCM

Proposed Algorithm and Architecture:

Yolov5:

An algorithm called YOLOv5 is used to identify and categorize objects in images and video streams. In order to anticipate object classes and bounding boxes in an image, it uses a deep neural network architecture. The YOLOv5 algorithm is capable of recognizing a large range of objects, such as humans, animals, cars, and other objects. The input image is divided into a grid of cells by the YOLOv5 algorithm, and each cell predicts a set of bounding boxes and object scores. After removing overlapping bounding boxes using nonmaximum suppression, the algorithm returns the last set of objects found. With its excellent accuracy and speed compared to other object identification algorithms, YOLOv5 is perfect for real-time applications. In addition, compared to other state-of-the-art algorithms, its model size is less, which enhances its efficiency and facilitates its installation on devices with limited resources.

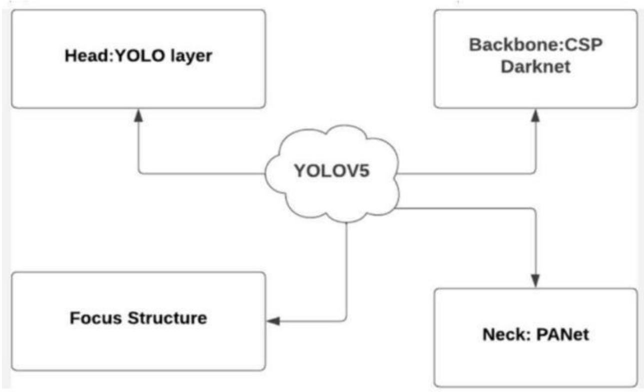

Fig.2.YOLOv5 (Architecture) [2]

CNN (Convolutional neural network):

CNNs are deep learning algorithms that are widely used to recognize photos and movies. They are made up of layers that extract data using convolution and pooling, followed by fully linked layers for prediction. Fully connected layers are used to aggregate information for exact predictions, pooling layers for downsampling, and convolutional layers for pattern recognition.

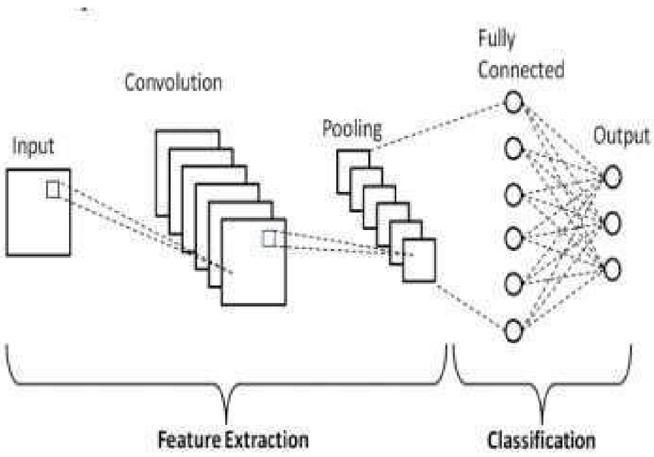

Fig.3.CNN(Architecture) [3]

5.RESULT ANALYSIS

The transfer of the file or image from the system is the initial stage in the execution procedure. Following that, two prediction results are obtained, with precision displayed in the upper left corner. One is accomplished through written means, while the other is achieved through auditory means. The Google Text to Speech Conversion Library is used to convert text communications into audio files. The correctness of the uploaded image is dependent by the photograph's angle and direction.

Figure 5 depicts a single bounding box that has the necessary precision for a single currency input. Figure 6 shows the output produced by numerous bounding boxes when several currencies are used as input. The bounding box's precision depends on the image's pixels and placement angle.

Fig.4.Test Images

SINGLE CURRENCY AS INPUT

Fig.5.Output of single note

MULTIPLE CURRENCY AS INPUT

Fig.6.Output of multiple notes

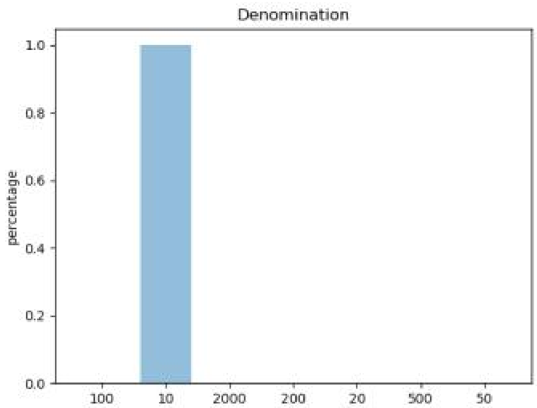

Fig .7.Accurately detects input image as 10-rupee note

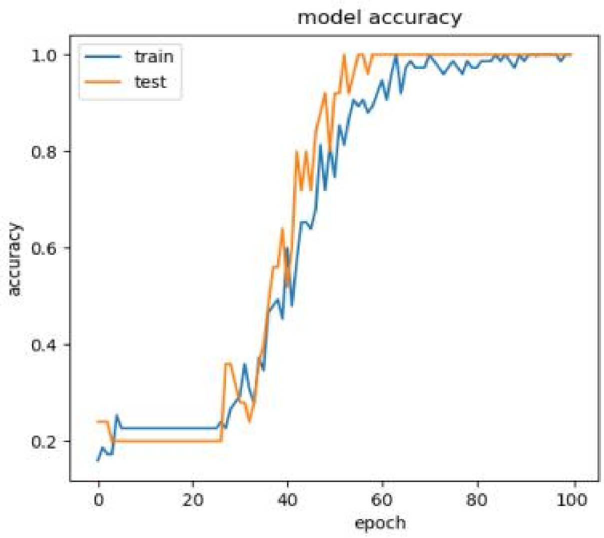

Fig .8. Accurately detects for multiple notes using train and test data

6.CONCLUSION

The proposed YOLOv5 model shows great recall and precision while identifying money bills. Out of 100 test data photographs, the model accurately recognized 80. A YOLOv5-native web application was developed to recognize banknotes with a high bounding box probability. The web program provides speech-out files for recently discovered English currency note labels. It is possible to extend the model to recognize foreign banknotes. Incorporating Optical Character Recognition (OCR) into the system is one technique to improve the model's performance.

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