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Currency Detection and Recognition System Based on Deep Learning

Ms. P. Divya Jenifar[1],Ms. V. Harinitha[2], Ms. M.D. Harshini[3],Ms. A. James Christiya[4]

[1]Assistant professor ,Department of Biomedical Engineering,Sri Shakthi Institute of Engineering and Technology,Tamilnadu,India.
[2,3,4]Final year students,Department of Biomedical Engineering,Sri Shakthi Institute of Engineering and Technology,Tamilnadu,India.

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Abstract -This paper suggests a method for recognizing currency through image analysis. The method relies on the three characteristics of color, height, and texture, which utilized for distinction. The method put forth in this document can be used to find the currencies of numerous nations. For the purposes of execution, only paper currencies from India are taken into account. This system, which employs the CNN (Convolution Neural Network), makes it simpler to check currency anywhere, at any moment. Every denomination of India was used in our testing, and the system was able to identify with 95% precision. To improve the technique's accuracy, a classification model is created using all of the previously stated factors. Features of paper money are crucial to this identification.

Key Words: Currency recognition, color, CNN, Open CV, ResNet.

1. INTRODUCTION

In the field of artificial intelligence, machines are capable of carrying out independently tasks that often call for human intelligence. Artificial neural network algorithms used in deep learning takes inspirations from the human brain to learn from vast volumes of data. Deep Learning executes a task repeatedly, each time producing results that are more accurate than the last, similar to how humans learn from their experiences. Utilizing an unstructured, linked, and varied data collection, machines can use deep learning to solve complicated issues. Data from an entity is typically unstructured since it can be found in many various formats, including text, photos, and PDF files. Unstructured data analysis is challenging; deep learning can be useful here.Deep Learning algorithms can be trained with a variety of data types and still produce insights that are useful for the task at hand.

Based on image recognition, several points of view were presented by examining the colour, design elements, and specific information of the currency, and then specialized identification techniques were provided. Methods for currency recognition were offered, including picture augmentation, rotation angle, and colour analysis of currency images. In a neural network, deep learning occurs. It requires a set of big data first. The accuracy of currency recognition could be continually improved by examining the training data set, and our expectations for the testing outcomes could be met. Convolutional neural network (CNN) is essential to the recognition process and can increase training accuracy by utilizing CNN models. As a feature extractor, CNN is used.

The data are extracted from the images by slicing the video into a single frame, it is first necessary to edit the images and make the image clearer to some extent, which also improves the accuracy after training. This is because when we collect data for currency recognition, we must first consider whether the size of the data set is sufficient. Overfitting is a risk that deep learning processes are subject to. It is simple to make the training process more difficult and time-consuming, while simultaneously allowing us to investigate drop technologies and prevent overfitting.

2. LITERATURE SURVEY

2.1.Based on Convolutional Neural Networks for Object Recognition

Asim Suhail, Manoj Jayabalan, and Vinesh Thiruchelvam, three researchers from the School of Computing at the Asia Pacific University of Innovation & Technology, claim that computer vision is getting better at segmenting, extracting features from images, and identifying objects in them. They believed that there is a growing interest in object detection across a variety of industries, including robotics, traffic monitoring, surveillance, and healthcare. Their key concern was being able to detect the object with more accuracy than usual. Researchers have worked hard in recent years to meet this problem. Review of the object detection method utilizing convolutional neural networks is presented in this article. In all types of object detection, CNN is useful.

2.2. Application Of Object Detection To Convolutional Neural Network

The latest ImageNet task on object detection from video (VID), in Kai Kang Wanli Ouyang Hongsheng Li Xiaogang Wang Department of Electronic Engineering's opinion, brings the object detection task into the video domain, where objects locations at each frame are required to be annotated with bounding boxes. They utilized the conventional mean average precision on all classes as the evaluation metric because the evaluation process for the VID task is comparable to that of the DET task.They made the decision to combine generic object tracking and still-image object detection to provide a comprehensive framework for the VID task. It is capable of object detector object discrimination.

2.3. Using VGG16, Deep Learning Based Indian Currency Detection for Visually Impaired

Banknote recognition is one of the main issues experienced by people with visual impairments, according to Nijil Raj N, Anandu S Ram, AneetaBinoo Joseph, and Shabna S of the International Journal of Recent Technology and Engineering. As a result, they have developed a system with an accuracy level of about 99.07%. According to their project, VGG 16, which is meant to be a pretrained model of a convolution neural network, is directly fed bank notes in various places. It is a DL method that accepts an input image and ranks the items in the image according to relevance. This allows it to distinguish between five different classes of notes, including the Rs20, Rs50, Rs100, Rs200, and Rs500 notes. Then, random photos are extracted from these note classifications. 15 additional photos in 11 locations are taken into consideration.

2.4. Detection of Banknote Portraits Using Convolutional Neural Network

According to Ryutaro Kitagawa, Yoshihiko Mochizuki, Satoshi Iizuka, Edgar Simo-Serra, Hiroshi Matsuki, Naotake Natori, and Hiroshi Ishikawa from Nagoya University's Department of Computer Science and Engineering, banknotes typically have different designs depending on their denominations.They made the decision to develop a banknote sorting system that could identify each banknote's picture and arrange it correctly. Their primary goal is to automatically detect portraits in sample banknotes in order to configure such a sorting system, with the intention of deploying it throughout the nation. They have utilized CNN to find portraits in a brand-new batch of currency [20]. Here, candidate regions are generated using a moving window so that all potential candidates can be methodically counted. CNN is used to determine the likelihood that a portrait is present in the candidate region.

2.5. Utilizing Covolutional Neural Networks to Identify Fake Currency Notes

The Automatic false Currency Recognition System was developed by Navya Krishna G, Sai Pooja G, Naga Sri Ram B, Yamini Radha V, and Raja Rajeswari P of the International Journal of Innovative Technology and Exploring Engineering (IJITEE) to determine if the currency is false or original. Conceptually, this approach is built on deep learning. This method can direct both humans and machines in identifying and figuring out whether the currency is phony. For the model data to be in a consistent format and for the training to be more efficient, accurate, and quick, perspective modifications must be applied to the image. A fake or original note can be identified in the end result by training an artificial neural network on a set of images of currency to predict which class the image belongs to.

3. METHODOLOGY

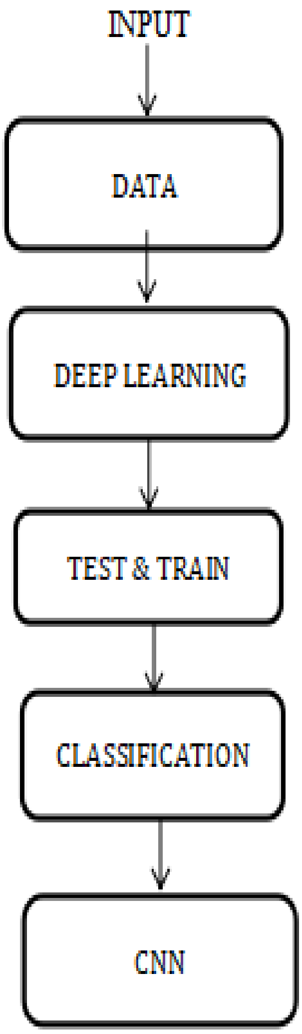

Fig 3.1 Flow chart

3.1 Dataset:

Indian money is the dataset in use. The collection includes different new Indian currencies, including the Rs. 10, Rs. 20, Rs. 50, Rs. 100, Rs. 200, Rs. 500, and Rs. 2000. The currency collection includes notes in various settings and lighting. Below is an example dataset for Rs. 100.

Fig 3.2 Data sets of Rs.100

3.2 Deep Learning:

A neural network with many layers capable of learning numerous images as the dataset is called deep learning. It has primarily been applied to speech, vision, object detection, and picture recognition. With deep learning, the back propagation algorithm is used to predict each layer's weights. distinct layers have distinct processing effects. Despite being extremely complex, the method has been used for image processing and recognition. Unsupervised learning (UL) and supervised learning (SL) are closely related in artificial neural networks (ANN). A neural network system based on Max Pooling Convolution was put forth in 2015 and has the potential to be used for object detection and picture recognition. Each neuron could be triggered through deep learning, but the complexity will rise as the levels rise.

Deep learning is much more effective than conventional machine learning techniques at resolving real-world issues. Deep learning is required in the case of ever-increasing big data to analyze and learn in a huge amount of comfortable data, combining deep learning and big data technologies. Deep learning has various levels of complexity and layers for different types of data, but as more data is collected, a neural network becomes simpler the more layers it has, which is one of the reasons why deep learning has become a widely used computing technology. However, compared to machine learning, deep learning has a much broader range of applications.

3.3 Test & Train

To train the ResNet pretrained model and produce the solution to the specified problem, a dataset is provided. A dataset of examples used for learning, i.e. to fit the parameters for a classifier, could be a training dataset.A dataset that is separate from the training dataset but has a comparable likelihood distribution to the training dataset could be a test dataset. The least amount of overfitting occurs when a model that fits the training dataset and test dataset well agrees. Overfitting is primarily shown by a considerably better fit of the training dataset to the test dataset.

3.4 Algorithm:

ResNet convolution neural network technique is employed in this process. It is an abbreviation for residual network, which is an already-trained model. Although there are various ResNets, ResNet_101V2 is used. A convolutional neural network with layer depths of 101 is called ResNet 101V2. A pretrained version of the network can be loaded onto a specific database's millions of images. This network can categorize images into various things, including pencils, keyboards, and other items.

3.5 Feature Set:

ResNet independently extracts the deep features. Each banknote's deep characteristics are extracted and put into different categories. The ResNet design comprises of a 1000-way softmax classifier, four fully connected layers, maximum pooling layers, and twelve convolutional layers. These levels enable the ResNet to extract detailed features from the banknotes. However, compared to alexnet, the current algorithm extracts fewer features from the banknotes.For higher accuracy, ResNet is therefore preferred.

3.6 CNN:

Deep comprehension neural networks include convolutional neural networks (CNNs). Consider CNN to be a machine literacy system that can accept an input image, apply (learnable weights and impulses) to colorful objects and characteristics in the image, and be appropriate to distinguish between them. CNN works by cropping away details from the pictures.

The following is included in every CNN

1. The grayscale input subcaste, which is a picture.

2. The affair subcaste's dual or multiple class marks

3. The retired layers consist of a fully linked neural network, pooling layers, complication layers, and ReLU (remedied direct unit) layers.

Realizing that Artificial Neural Networks (ANNs), which are made up of several neurons, are unsuited to extract features from a picture, is crucial. Then a mix of a pooling subcaste and a convolutional subcaste is used. Additionally, bracket cannot be carried out by the pooling or complication layers; therefore, a fully linked neural network is required. CNN's task is to resize the images to make them easier to reuse without obscuring features necessary for precise categorization. This is crucial because the system needs to be scalable to large databases.

3.7 Pooling:

The complicated point, which is also referred to as the activation maps, is subjected to non-linear down sampling by the pooling subcaste. The main goal of this is to lessen the computational complexity required to reuse the enormous amount of data that is connected with an image. Pooling is never necessary and is always avoided. Pooling is typically split into two categories. Average Pooling parses the values covered by a Pooling Kernel, while Max Pooling gives the maximum value from the area of the image covered by the Pooling Kernel.

3.8 Image Leveling

The incident must first be pooled before being transformed into an irregular structure that an artificial neural network can use for bracket. Depending on the issue statement, different numbers of neurons and thick layers may exist. The algorithm is continuously assisted in preventing overfitting by a drop out subcaste. Dropouts use all of the activation maps during assessment but only use a portion of them during training. It reduces neuronal correlation to avoid overfitting.

3.9 Working of CNN

A CNN can have many layers, and each subcaste teaches the CNN to respect the various characteristics of an input image. A sludge or kernel is applied to each picture to create an affair that improves and becomes more detailed with each subcaste. In the lowest layers, the pollutants might first appear as introductory traits. The complexity of the pollutants grows with each new subcaste as a result of the need to check and identify features that specifically represent the input item. As a consequence, the posterior subcaste receives its input from the incompletely recognized image from each subcaste's affair, also known as the convoluted image. The final subcaste, which is an FC subcaste, is where the CNN identifies the image or object it stands for. The input image is recycled during complication by a variety of various pollutants. Each sludge carries out its task by activating particular parts of the picture, then sends its message to the sludge in the rear subcaste. As each subcaste learns to respect distinguishing characteristics, the processes are repeated for dozens, hundreds, or even thousands of layers. Once all of the image data has been recycled through all of CNN's layers, it is finally able to recognize the entire object.

4.RESULTS AND DISCUSSION

The webcam immediately opens as soon as the program is run, and the notes that need to be recognized are now in front of the camera. The image is then saved so that it can be used as the input image. The amount on the note is converted to voice and the note is recognized and presented in the output. Below are some of the output options.

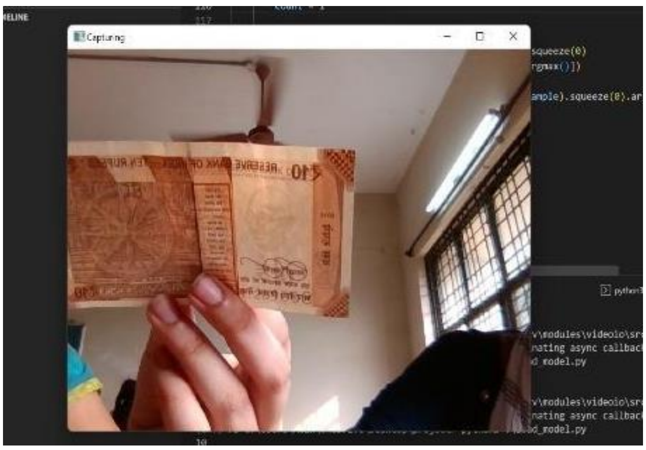

Fig 4.1 Rs.10 Detected

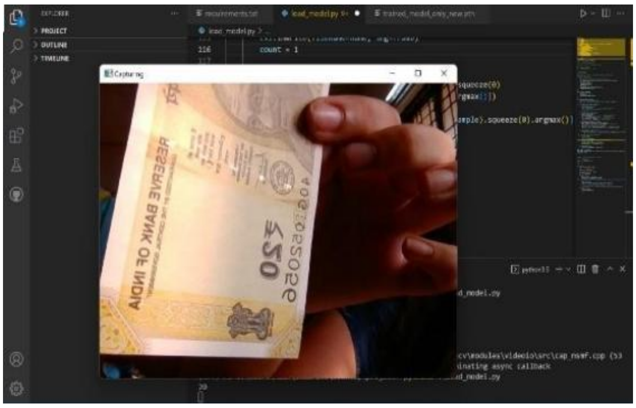

Fig 4.2 Rs.20 Detected

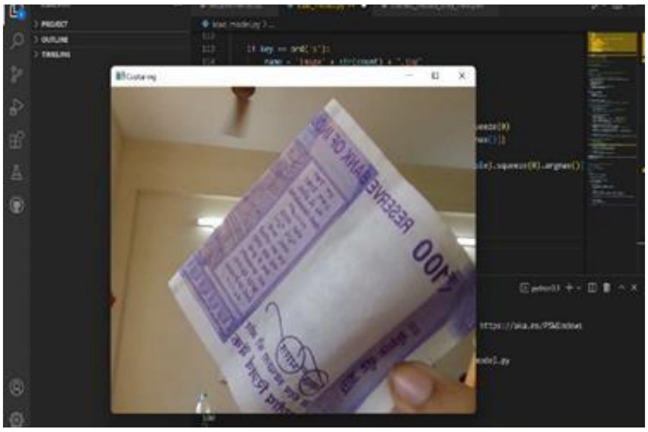

Fig 4.3 Rs.100 Detected

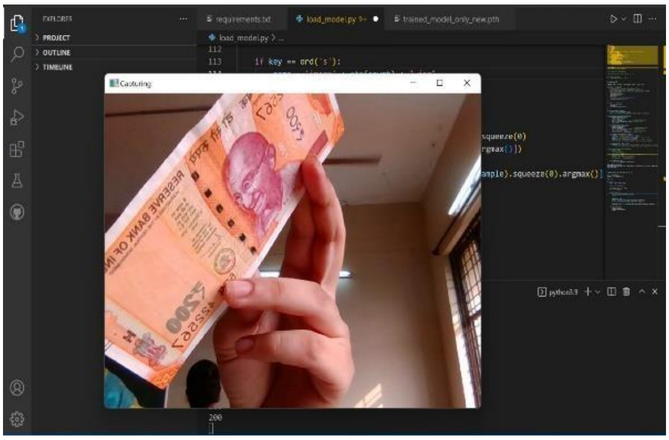

Fig 4.4 Rs.200 Detected

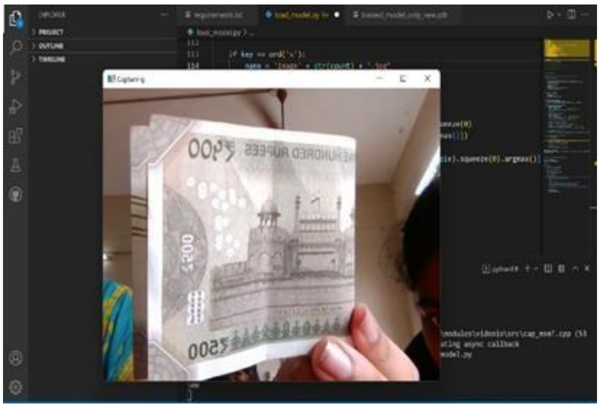

Fig 4.5 Rs.500 Detected

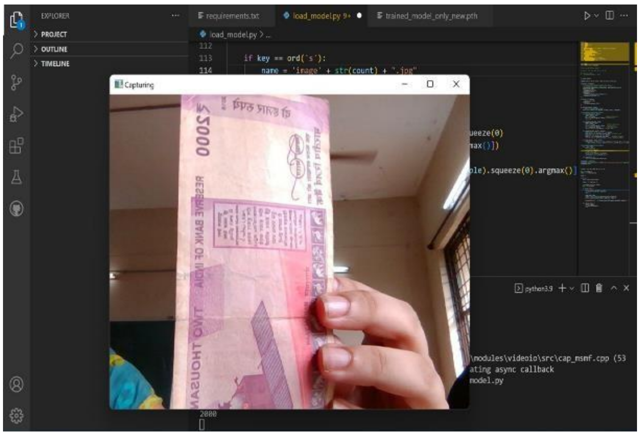

Fig 4.6 Rs.2000 Detected

Our approach suggests a vision-based deep learning method that can recognised and categories well-developed Indian Currencies. Deep features from the input image were discovered to be extracted using ResNet. Better accuracy is provided by our system (96.07%). The current system makes use of Alexnet but with less features extracted. ResNet, which can extract features with deeper depth, is employed as a result.

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