

# INDIAN CURRENCY IDENTIFICATION FOR VISUALLY IMPAIRED

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## ABSTRACT:

Major difficulties faced by blind people is unable to identify the value of currency due to some similar attributes such as texture and size. Due to this the blind people finds difficulty in identifying the currency value. This application helps blind people in identifying the currency value. First they will give command as open camera and then the camera will be opened and it will capture the image of the currency automatically.

**Key words:** Preprocessing data, Image Acquisition, CNN, Image augmentation, Visually impaired, currency identification

## 2. INTRODUCTION:

The assistive technology is one in which the person can overcome his disability to face his obstacles. Recently, the attributes of Indian currency were changed, due to blind people are facing many difficulties in identifying the value of the new currency. Though the colors present in currency are useful for people with good eye sight but this is not benefitted for blind people. These people find it difficult to differentiate the new currency. So our project helps visually impaired people by overcoming his difficulties in identifying the value of the currency and can lead their life without depending on others both financially and socially.

## 3. LITERATURE SURVEY:

There have been a slew of proposed currency recognition systems. Using computer vision, the authors identify and recognise four distinct currencies. Texture, colour, and shape of four different currencies were used to distinguish the features. For classification, they employ an Artificial Neural Network. The accuracy rate was on average 93.84 percent.

Using a dataset of Jordanian currency, Iyad et al. developed a mobile currency

recognition system. The scale-invariant feature transform (SIFT) algorithm was used to implement this approach on a smart phone using the Jordanian dataset. For paper money, the device had a precision of 71% and for coins, it had a precision of 25%.

The author suggested a mobile paper currency detection device for Saudi Arabian currency. The method for recognising paper currencies is focused on some intriguing characteristics and similarities between two pictures. For classification, it employs the Radial Basis Function Network. For Normal Non-Tilted Images, the device has a recognition accuracy of 95.37 percent, 91.65 percent for Noisy Non-Tilted Images, and 87.5 percent for Tilted Images..

Based on size information and multi-template correlation matching, Sungwook et al. proposed an efficient and fast algorithm. Since different banknotes have different sizes, this information was considered significant. This approach was evaluated with 55 currencies from five countries in 30 separate classes: EUR, KRW, RUB, CNY, and USD. This method's findings were 100 percent classifiable.

For identifying paper currencies, a non-parametric approach is suggested. For each type of paper currency, the proposed approach is focused on the construction of a non-parametric model.

Averaging all available samples of a single banknote yields the model. Finding the coefficient values between the banknote and the non-parametric models and matching on these values allows the checked banknote to be recognised. To get a good result when capturing currency, make sure the camera and currency are aligned horizontally. Three types of Saudi Arabians are used in this process.

Easy currencies CRSF were used by Noura et al. This approach compares the proposed method to this method which uses the

same dataset as the proposed method. Image segmentation, equalisation, and region of interests (ROI) extraction are some of the basic techniques used in the proposed scheme, and the prototype is then matched based on similarities between the captured image and the database dataset.

Farid and colleagues developed an artificial vision-based recognition system for Mexican bank notes. This method demonstrated that the texture and colour features of Mexican banknotes can be used to classify them. For the identification process, this approach employs the RGB colour model and Local Binary Patterns. This approach has a low degree of accuracy.

Junfang et al. used a new LBP algorithm for characteristic extract called block LBP algorithm. It's focused on the conventional LBP (Local Binary Pattern) process. This method is both easy and quick. The experimental results revealed that this improved method has a high recognition rate, as well as a robust response to lighting changes and noise, with an accuracy ratio ranging from 92 to 98 percent..

#### **4. EXISTING SYSTEM:**

Many of the methods for recognising currencies are designed for use on desktop computers. For mobile devices, however, there are both commercial and non-commercial currency recognition apps. LookTel, Money Reader, and IDEAL Currency Identifier are all examples of this type of app. The majority of the preceding approaches formulate the solution as one that is educated offline with sufficient

positive and negative examples. The downside is that correctly identifying currency necessitates a high-resolution camera and a lot of light. Bills must be mounted on a flat surface, horizontally, and in good lighting in some applications. It can't tell whether a bill is wrinkled or worn.

#### **5. PROPOSED SYSTEM:**

There are various applications for visual object recognition on cell phones. The issue of currency bill recognition on a low-end cell phone is the subject of this project. For the visually impaired, this is an urgent requirement. Around 285 million people worldwide are believed to be visually impaired, with 39 million blind and 246 million suffering from poor vision. The visually impaired cannot identify currency bills based on variations in texture or length. Furthermore, unlike coins, bills are difficult to discern by touch. On the bills of various currencies, some distinctive engravings are printed, but they wear away over time.

Here the proposed system uses CNN model to identify the appropriate currency. It gives accurate results on low-end mobile phones also.

#### **6. WORKING:**

This consists of the three modules

- Dataset Collection
- Creating AI Model
- Integrating AI Model with Android environment

### Dataset Collection

A collection of data is known as a data set. In other words, a data set is the contents of a single database table or statistical data matrix, where each column represents a specific variable and each row represents a specific member of the data set in question..

A training data set is needed for Machine Learning projects. It's the data set that was used to train the model to perform different tasks. ML is highly dependent on data; without it, a "AI" would be unable to understand. It is the most important factor that allows algorithm training to take place. If your data set isn't good enough, it doesn't matter how good your AI team is or how big your data set is, your AI project as a whole would crash.

We have two sub modules in this dataset collection module. They are

- Image acquisition
- Preprocessing information

#### Image acquisition

In our project, we are going to classify the Indian currency values and express as voice output to help visually impaired peoples. So we captured video of Indian currency 10, 100 and 500 rupees notes in different angles and given as input. Then we convert it as image using frame based image conversion. Here it takes 24 images as input from 1 Minute video.

### Preprocessing data

Image data augmentation is a technique for the the size of a training dataset artificially by making changed versions of the images in the dataset.

More data can help deep learning neural network models become more skilled, and augmentation techniques can help suit models generalise what they've learned to new images by creating variations of the images..

The ImageDataGenerator class in the Keras deep learning neural network library allows you to fit models with image data augmentation..

This process is divided in to eight parts, they are:

- Image Data Augmentation
- Sample Image
- Image Augmentation With ImageDataGenerator
- Horizontal and Vertical Shift Augmentation
- Horizontal and Vertical Flip Augmentation
- Random Rotation Augmentation
- Random Brightness Augmentation
- Random Zoom Augmentation

### Creating AI Model

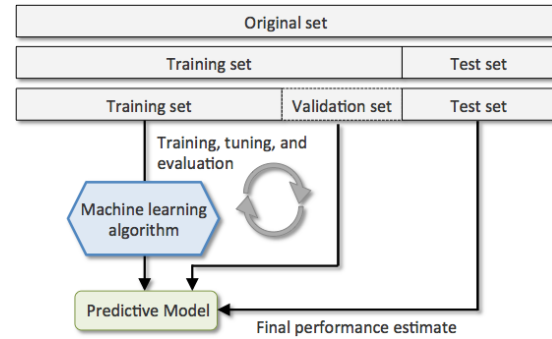
We always depend on data when working on AI. We use three separate data sets for preparation, tuning, model selection, and testing: the training set, validation set, and

testing set. Validation sets are used to choose and tune the final ML model, for your knowledge.

You may believe that collecting data is sufficient, but this is not the case. Classifying and labelling data sets takes up the majority of our time in any AI project, especially data sets that are accurate enough to represent a practical vision of the market/world.

We'll need two datasets: a training data set and a test data set, since they'll be used for various things in your AI project, and the progress of the project is heavily dependent on them.

1. The training data set is used to teach an algorithm how to learn and generate results using concepts like neural networks. It contains both the planned and input data. The majority of the data, roughly 60%, is comprised of training sets..
2. The test data set is used to see how much your algorithm learned from the training data set. We can't use the training data set in the testing stage of AI projects because the algorithm would already know the expected performance, which isn't what we want. Twentypercent of the data is made up of testing sets..



**FIGURE 6.7 Process of creating AI Model**

In our project we need to classify objects from captured images so we used convolutional Neural Network(CNN)

### Convolutional Neural Network (CNN)

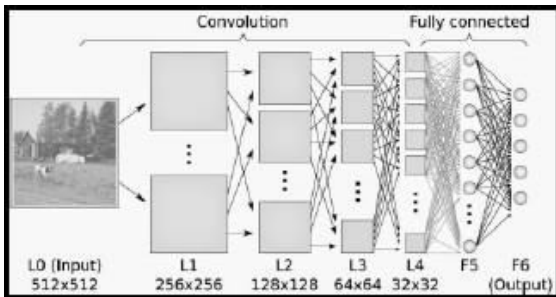
As the name implies, neural networks are a machine learning technique that is modelled after the structure of the brain. It is made up of a network of neurons, which are learning units. These neurons learn how to transform input signals (such as an image of a cat) into output signals (such as the mark “cat”), which is the foundation for automatic recognition..

The communication pattern between the neurons of a convolutional neural network (CNN, or ConvNet) is inspired by the organisation of the animal visual cortex..

CNNs are made up of recurrent blocks of neurons that are applied through space (for images) or time (for time) (for audio signals etc).These blocks of neurons can be interpreted as 2D convolutional kernels that are applied

repeatedly over each patch of the image in the case of photos. They can be thought of as 1D convolutional kernels that have been applied through time windows for expression.

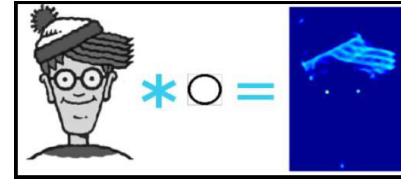
The weights for these repeated blocks are 'shared' at training time, which ensures that the weight gradients learned through different image patches are averaged.



**FIGURE 6.8 Finger Spelling American Sign Language**

**Convolution**

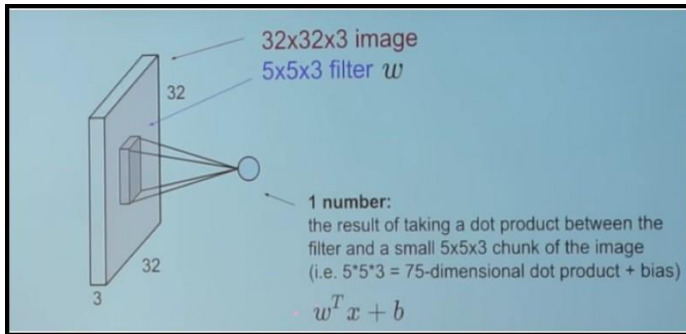
Convolution filters are the very first layers that receive an input signal. Convolution is a method in which a network attempts to mark an input signal by referring to what it has learned previously. The “cat” reference signal will be blended into, or convolved with, the input signal if it looks like previous cat images it has seen before. The output signal is then sent to the next stage..



**FIGURE 6.8 Convolving Wally with a circle filter. The circle filter responds strongly to the eyes.**

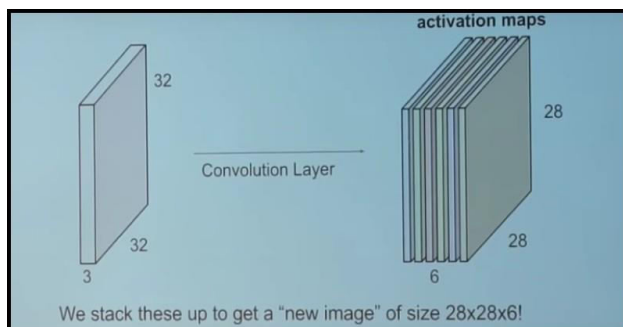
Translational invariance is a nice property of convolution. In a nutshell, each convolution filter represents a feature of interest (e.g., whiskers, fur), and the CNN algorithm learns which features make up the reference picture (i.e. cat). The output signal strength is determined by whether or not the features are present, not by where they are located. As a result, a cat may be sitting in a variety of positions and still be recognised by the CNN algorithm..

Let's assume we use a 5x5x3 filter to convolve a 32x32x3 image (32x32 image with three channels: R, G, and B). We apply the 5\*5\*3 filter to the entire image, taking the dot product between the filter and chunks of the input image along the way..



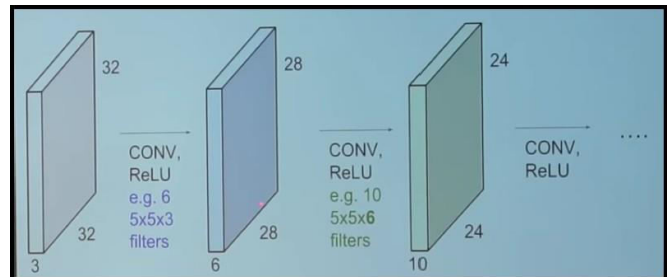
**FIGURE 6.9 Dot Product of Filter with single chunk of Input**

A group of independent filters make up the convolution layer (6 in the example shown). Each filter is convolved with the image separately, resulting in six feature maps with the form 28\*28\*1..



**FIGURE 6.10 Input Image convolving with a Convolutional layer of 6 Independent filters**

The CNN may be made up of many Convolutional layers, each with a different number of independent filters. The effect of two Convolutional layers with six and ten filters, for example, can be seen in the diagram below..

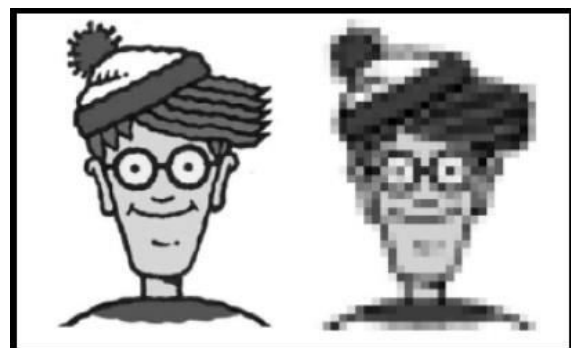


**FIGURE 6.11 Input Image Convolving with two Convolutional layers having 6 and 10 filters respectively**

These filters are all randomly initialised and become our parameters, which the network can learn later..

### Sub-Sampling

To reduce the sensitivity of the filters to noise and variations, the convolution layer's inputs can be "smoothed." Sub-sampling is the term for the method of smoothing a signal by taking averages or the maximum value over a sample. Sub-sampling methods (for image signals) include shrinking the image size or lowering the colour contrast across the red, green, and blue channels.

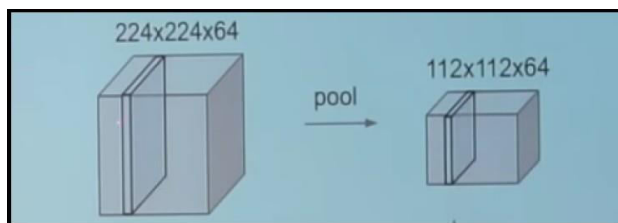


**FIGURE 6.12 Sub sampling Wally by 10 times. This creates a lower resolution image.**

### Pooling

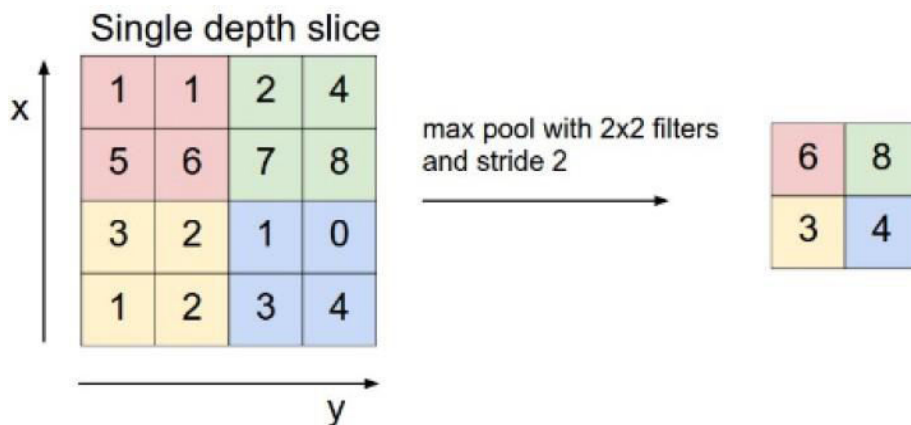
Another part of a CNN is the pooling layer.

Its aim is to gradually shrink the representation's spatial size in order to reduce the number of parameters and computations in the network. Each function map is treated separately by the pooling layer..



**FIGURE 6.13 Pooling to reduce size from 224x224 to 112x112**

The most popular pooling method is max pooling, which uses the limit of an area as its representative. A 2x2 area, for example, is replaced by the maximum value in the following diagram.



### 6.1.2.1.4 Activation

The activation layer regulates how the signal travels from one layer to the next, simulating the firing of neurons in our brain.

More neurons can be activated by output signals that are closely linked to previous references, allowing for more effective signal propagation and recognition..

The Rectified Linear Unit (ReLU), which is preferred for its faster training speed, is compatible with a wide range of complex activation functions to model signal propagation..

### Fully Connected

The network's final layers are completely linked, which means that neurons in previous layers are connected to neurons in subsequent layers. This is analogous to high-level thinking, which explores all possible paths from input to output.

### Integrating AI Model with Android environment

This module will show you how to attach your AI model to the Android world. Following the training process, the AI model is output in the form of a Tensorflow model, i.e. ProtoBuf (.pb).

With the Android Studio platform, the device is unable to import this format directly. As a result, we use the TFLite converter, whose performance will be used to integrate with the Android environment..

A TensorFlow model is converted into a TensorFlow Lite model by the TensorFlow Lite converter (an optimised FlatBuffer format identified by the .tflite file extension). The converter can be used in one of two ways.

1. **Python API (recommended):** This simplifies model conversion as part of the model creation pipeline, as well as implementing optimizations, incorporating metadata, and many other functions.
2. **Command line:** This only allows you to convert simple models.

### 7. ARCHITECTURE DIAGRAM:

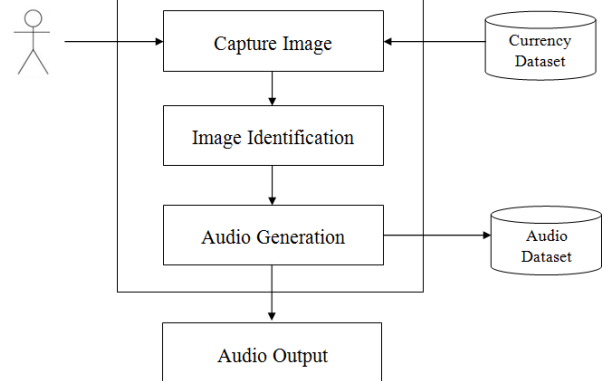


FIGURE 7.1 Architecture diagram

### 8. ADVANTAGES:

This programme is also compatible with low-end cell phones. The accuracy is better than previous approaches. This programme should be available in a wide range of circumstances

### 9. CONCLUSION:

In this project, the framework has proposed a mobile application for currency recognition that recognises Indian currency to assist blind people in their everyday lives, in order to solve the common aiming issue for blind users. The final product in this project is regional audio.

This project will be expanded so that the classification can be used to compare original and counterfeit currency. International languages can be introduced that can be used all over the world. To establish currency note recognition on a low-cost cell phone for visually impaired people, and to alert them with a voice note in their native language. It could be expanded in



the future to include foreign currency recognition.

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