2. BACKGROUND

In terms of currency recognition, the attempts are being made since 1993 to make the life easier for the visually challenged people. The currency recognition is mainly based on object detection and image feature extraction. So, the following text discusses the work done so far in the areas of currency recognition, object detection, and image feature extraction. Next section discusses the currency recognition work that has been carried out for the Indian currencies. The third section describes the currency recognition tools and Apps available in the market. In the end, the final section tells about the tools and technologies used in this work.

2.1 WORK CARRIED OUT ACROSS THE WORLD

In 1992, Johan Plomp introduced an image understanding system [1]. They described object-oriented libraries containing a definition of image features, operators to deal with that feature and a storage framework. Once the image features are created, links are established from these created features to source features and relation can be established.

Frank Brill, in [2], gave a genetic technique for feature selection for neural network classifiers. In their proposal, they introduced two novel techniques. To reduce the significant computation, they used an approximate evaluation method and nearest-neighbor classifier to evaluate the feature set. In the second phase, they gave a training set sampling method to select the features that are better than occasionally good features.

The first ever direct attempt in currency recognition was made in 1993 by Fumiaki Takeda et. al. They proposed a currency recognition system for US Dollars using the neural network with random masks [3]. They developed a downsizing method for the neural network by slab-like architecture. They noticed that even if the inputs are different, the same slab values can be obtained. Here, the slab values are the sum of input pixels. To avoid any problem, they introduced random masks. They showed that on a 32-bit computer using conventional bill recognition system, their algorithm worked fine since all US Dollars currencies are similar to each other and have similar color tone.

Davi Geiger and his colleague, 1993, proposed the renormalization method for scaling images and image features. They proposed this to obtain high-quality images and image features when the images are scaled. They used Markov image model with

Gaussian noise and a local parameter for discontinued images. They derived self-similar properties of the model by averaging over half lattices. They called it as renormalization group. In this, two multi-scaled parameter structures were obtained, one for images and other for image discontinuities. The images produced after scaling while using renormalization group were smooth and good in contrast. This paper served the purpose of keeping image features intact even after enlargement [4].

A genetic algorithm and neural network based optimized mask method was another successful attempt by Fumiaki Takeda and Sigeru Omatu in 1995 for paper currency recognition. They treated position of the masked part as gene and sampled parental masks along with the operations like crossover, selection, and mutation. They revealed that the repetition of such operations optimizes the masks and currency recognition time can be shortened. To improve the recognition system, they gave another method to classify the US and Japanese currency by speeding up the recognition. They used time series and Fourier power spectra directly as input to the neural network. They reduced the input scale to the neural network and thereby preventing the growth of recognition. For recognition, it uses the only a subset of the original dataset which is generated using random masks [5] [6].

Angelo Frosiniet et al., in [7], proposed a neural-based recognition and verification system named BANK (Banknote Acceptor with Neural Kernal) which was based on low-cost optoelectronic devices. It produces a signal associated with the light reflected by the banknotes. The classification and verification are carried out by a group of multilayer perceptrons which are controlled by an external real-time microcontroller based algorithm. The verification phase is dependent on auto-associators to generate separation surfaces in the patterns.

In [8], Greg Pass and his teammates at Cornell, gave a histogram based method to compare images. They classified each pixel in the specific color bucket as a coherent or incoherent pixel based on a similarly-colored region. A Color Coherent Vector (CCV) keeps a number of coherent vs. incoherent pixels for each color. Having this gives finer separation of pixels than the histograms. On a standard workstation, at a rate of 5 images per second, CCV can be computed. They proved that CCV gave better results than the histograms.

For image feature detection, in [9], Sugata and Rajiv introduced a model-based approach for image content extraction. In their method, for each type of feature, a piecewise model is developed to characterize local intensity function for an image. They used a Zernike-moment-generating polynomial to estimate the model parameters and generate the desired feature map. Moment-based detectors extract various kinds of primal sketches from images. The main advantage of parametric-model is that it is possible to extract complete information of the image, especially in high vision image.

Jun Yuang et al. implemented the first ever Bag of Visual words in their work [10]. They said that the visual representation of the dimension, the weight of visual words are important and may vary. They implemented it with the analogy of word dictionary using TRECVID and PASCAL and showed that it improves the accuracy of image classification.

Jing Huang et al. at Cornell gave the concept of color correlogram in [11] for indexing and image comparison. It refines the spatial correlation of colors and gives an inexpensive method for image content retrieval. The correlogram is robust in a way that depending on the viewpoint positions, it adjusts the changes in the appearance of the images and compares images accordingly.

To address the fundamental issue of image content retrieval, Wei-Ying Ma and Hong Jiang Zang made a comparison of some commonly used color and texture features of a large collection of image data. They used histogram, moments, coherence vectors and correlogram in the context of different color spaces and quantization [12]. They compared Tamura Features, edge histogram, MRSAR, Gabor texture, wavelet transform, etc. and benchmarked the experimental results for image-content retrieval.

Gian Luca Foresti, in his work of object recognition, developed a system for real-time object recognition. He considered statistical morphological skeleton and noise robustness for both object recognition and tracking. Recognition is obtained by comparing an analytical approximation of the skeleton extracted from the analyzed image [13].

In their work for recognition of paper-based currency, Masahiro Tanaka and his colleagues gave a two-stage process for currency recognition by image processing, namely recognition, and verification. They claimed that the two-stage process improves accuracy [14]. They introduced a verification step using Gaussian distribution using probability density to transform the input data to lower dimensional space. This structure, they, named as a hybrid neural network and proved accurate and computationally small.

In [15] 1999, Jae Yeon Lee and his team-mates gave fast retrieval method for image features. The method, they gave, uses scalar values induced from image vectors. The scalar values are independently stored as indices to target feature vectors. This improved the searching 25 times than the existing method.

C Papageorgiou et al. in their work [17] at MIT, in 2000, developed a trainable system for object detection in unconstrained and cluttered scenes. In this, the object is represented in terms of an over a complete dictionary of local, oriented, multiscale intensity difference between adjacent regions, efficiently computed as the Haar wavelet transform. This learning approach gives a model trained by support vector machine. They also quantified how the representation affects detection performance by using some alternate representations like pixels and principal component.

In his work [18] for multiple currency recognition, especially Euro currency, Fumiaki Takeda in 2000, gave an enhanced neuro-recognition system to increase more number of patterns in currency recognition. Here, they used an axis-symmetrical mask and two image sensors. Of the two sensors, one is used to discriminate between a known image, and the other one is used for exclusion of an unknown image. This system was effectively delivered for Euro currency in 2002.

J Sullivan and his team-mates in [19] at Oxford presented a Bayesian approach using a learned probabilistic model of image filter-blank output and Monte Carlo method to improve efficiency. They created a probabilistic account of image data using its intensities. However, they claimed that they did not fully address the issue of statistical independence. They applied a bank of filters to each image whose output is statistically independent. The responses of individual filters and their distributions are learned from training data. They are used to define a joint distribution for the output of a filter bank which they used for object localization.

In a feature selection scheme [20], Jane You et al., three primary issues are addressed. First, image feature extraction and representation, second, similarity measure and the third search method. A statistically based feature selection technique has been proposed to select the most appropriate features of an image for image indexing and similarity measure as well. They also proposed a discrimination function to enhance image feature points using image decomposition and contextual filtering. In addition to this, they also used a feature component code to ease the hierarchical search for best image matching.

Ali Ahmadi and his group have proposed a principal component analysis based neuro-classifier. Here, data is acquired through some advanced sensors and preprocessed to make an array of pixels. They deployed the PCA algorithm to extract the main features of data and reduce the data size. Along with this, an LVQ network model is used as the main classifier system. It has been proved that the reliability has been increased up to 95% when the proper number of PCA is taken [21].

For fast content-based image retrieval [22], Mira, Jesse, and Laurence in 2002 proposed an approach based on Quasi-Gabor Filter and dimensionality reduction. They addressed the three basic problems of high computational time, high dimensionality of data and image comparison with consistency in human perception. To decrease the computational time, they gave a strategy to extract the image features with higher accuracy. They proposed reward-punish algorithm to reduce the dimensionality. Here, they used the concept of weighting the features of the extracted image.

Sanghmitra and his colleague developed automatically evolving genetic clusters for image classification [23]. They used the Davies-Bouldin index for cluster verification. They used real-life data for classification purpose. Those images were satellite images of Kolkata city. It was used for land images.

In [24], Ali Ahmadi discussed the reliability of the neuro-classifiers for paper-based currency recognition. They used a local Principal Component Analysis (PCA) to remove the non-linear dependencies among the variables and to extract the important features of the data. In this method, the data space is divided into the self-organized map, called SOM, and on each region, PCA is performed. Later, to classify, an LVQ (linear Vector Quantization) is used. They tested it on 1200 samples of USD to check the reliability of the classifier, and it was near about 100%.

Talking about a statistical method for image feature extraction using wavelet domain [25], Hua Yuan and his teammates, in 2003, proposed a content-based image retrieval system. They developed a two-component Gaussian model for image characteristics in the wavelet domain. They used the Expectation-Maximization algorithm to build the indexing feature space for image retrieval. To check the performance of the algorithm, they used the Brodatz image database and proved its efficiency with less number of features in feature space and yet having better accuracy concerning other algorithms in its category.

In their work [26] about currency recognition using the neural network, Er-Hu Zhang et al. talked about extracting information from the images with noises. They gave a method to remove the impact of noises in images using the linear transformation of image gray. They used edge detection to obtain edge characteristics from images and divided that information into different areas to get the number of edge characteristics pixels in those areas. These pixels are used as input vectors to the neural networks and using three layers BP NN sorting recognition, the currency is identified.

D Guillamet et al. [27] worked on non-negative matrix factorization for preprocessing purpose. They employed this technique for dimensionality reduction in the form of weighted NMF. NMFs are represented in the form of color histograms. They used a hybrid approach with principal component analysis to improve classification accuracy.

Soo and colleagues implemented a content-based image classification technique divided into two parts. In the preprocessing part, foreground and background are separated using region segmentation. The wavelet transform is applied to get the features of the images and then the neural network is applied to label the image. They used 300 training and test data and proved 81% accuracy [28].

In [29] 2004, Feng-Cheng Chang and Hsueh-Ming Hang gave a new approach to content-based retrieval using positive and negative feedback. The most difficult task in content-based retrieval is to gain the user perception in the images. They considered sparse features of images to be less important and defined image feature stability to calculate the similarity measures in images. In addition to this, they also employed negative feedback to improve the searching while comparing the appropriate image content.

Carsten Rother and his team developed an efficient algorithm for background subtraction using graph cut theory [30]. They used graph cut iteratively find the region of interest and optimized it for region matting to find the boundary of the object from the background. They tested it for complex objects for the same and proved it better for background removal.

In Phase Spectrum based image feature extraction [31], Yaoxin Lv et al. proposed illumination free image extraction. In this, they used phase-only reconstruction and phase congruency for image extraction. They first construct the image using unit magnitude and original phase spectrum. Then by applying a Gabor wavelet, to calculate the phase congruency, the illumination free image is retrieved. This technique was used in face recognition.

In his doctoral thesis in 2006 [33], Dimitri presented the concept of a bag of local features for image classification irrespective of the point of correspondence and in case of occlusion or clutter. He also gave a hybrid approach of feature vectors along with a bag of features to improve classification accuracy.

Tomas used Ant Colony Optimization for image labeling. They found that automatic clustering in images is quite difficult. To achieve automated clustering of images, they used ACO along with k-Means. This approach showed promising results by achieving 80% around accuracy [34].

For object localization by subspace clustering, C Bouveyron and colleagues at INRIA presented a probabilistic way of object localization [35]. This includes subspace clustering and discriminative clusters as well. They used SIFT as a local descriptor for recognition since they are high-dimensional and live in different low-dimensional spaces. To address the dimensionality problem, they employed a high-dimensional data clustering method. They evaluated the discriminative capacity of the clusters and the same is used to calculate the probability of local descriptor being part of an object. The experiments were performed on Pascal 2005 dataset for performance evaluation.

In their survey article [36], Lu and Weng wrote that for multisource data, neural, decision tree and knowledge-based classifiers are better. They also noted that the integration of GIS, Expert system, and remote sensing would be helpful in image processing, but uncertainty in images highly affects the classification accuracy.

For accurate localization of objects, Marcin and Cordelia at INRIA developed a method that uses shape masks. In their method for determining the outline of the objects, no hypotheses parameter space is used. Here, the algorithm directly creates, evaluates and clusters the shapes. They claimed that it produces better output for object localization. They evaluated their approach on natural scenes Graz-02 dataset of objects, and the results were promising [37].

In [38] their image retrieval algorithm, Pengyu Liu et al. used feature statistics to extract the images from the given input. They used low-level features of an image like color, texture, shape, etc. for image retrieval. They used image texture characteristic to define image feature statistic. In addition to this, using image feature weight assigned to the various above mentioned features and by combining, they made image retrieval easier and better.

At NOKIA research center, Wei-Chao Chen and his teammates developed a robust image feature extraction method [39]. They implemented their SURF algorithm for computing the image features on NOKIA mobiles. Having captured the image, they calculated interest point, repeatable angle, and descriptor under the SURF algorithm. With this, matching the image with the feature database, the approximate nearest neighbor is decided. After performing geometry consistency check, the actual image objects are identified. Their algorithm has been used in image search, objects recognition and augmented reality applications.

Hassanpour and Hallajian, in [40] 2007, proposed a new feature extraction technique using texture characteristics for recognition. They employed a hidden Markov chain to model the texture of paper-based currency in a randomized process. They tested the method on more than 100 denominations of paper-based currencies of the different countries like USA, EU, UAE, and Iran.

In [41] any pattern recognition system, dimensionality reduction is the most important part and plays a vital role in image identification. For face recognition, Hamidreza used genetic algorithm based ACO algorithm to find relevant features. They used a length of feature vectors as heuristics so that without having any feature knowledge the system can easily find the optimal subset of features to label the image.

Wang and Liew, in their work [42], used information based color representation for image classification. They stated that the histogram of high-resolution images contain redundant information while same for low-resolution images do not contain enough information to classify the images properly. With this in mind, they proposed a method that takes the correlation between the neighboring components of the color histogram and removes the redundant information from it. For this, they generate a high resolution uniformly quantized histogram from the captured image. Then redundant bins are removed, and correlated bins are combined. This is done to increase the accuracy of classification. This information is used to evaluate the classification capacity of the feature set and iteratively the algorithm generates the histogram with its corresponding features. They proved its accuracy by implementing it on adult images to classify the images into benign and erotic images. For classification purpose, they used Ada-boost and SVM classifier.

For outdoor scene classification, Demir and Selim used a bag of regions as a classifier [43]. They created two types of classifiers: one, for images having uniform regions based on color and textures and the other, for the items having different structures in the images. They created two type of bag of words, a bag of independent regions and bag of region pairs. They use a Bayesian classifier for the final classification.

Qingjie Zhao et al. discussed image features in Robot vision system. They talked about geometry moments and Eigen-space transformations and identified them as vital features to recognize an image. This can help in avoiding unnecessary computation and make image feature extraction easier. They also proved that moment features are sensitive to external disturbances and Eigen-space transformations are anti-noise [44].

Xu Li, in his paper [45], proposed a currency reader based on a mobile camera for visually challenged people. This currency reader is specially made for US currency. It performs real-time processing on the captured image of currency and tells the denomination. He developed background subtraction and perspective correction algorithm for currency identification. For training purpose, an efficient Ada-boost framework is used. It processes ten frames/second and achieves a false positive rate of 10-4.

An image is captured via camera, and that image input is given for processing in Nurlaila's work [46]. In the processing phase, the image is converted into binary and grayscale. The region of interest is cropped, and various functions like dilation, erosion, threshold, and complement are performed on it. Later, a three-layered ANN is used wherein; the first layer processes the weights by a nonlinear function. Interconnection weights again multiply these and go to the second layer. The same process is repeated at the third layer which is the output layer. The output gives the denomination of the currency.

In his work [47], Yun Fu stated that image classification highly depends on the data structure, similarity or distance metric, distinguishable subspace, etc. He proved that correlation-based similarity metric with supervised learning improves the classification accuracy with a significant amount. They gave a new approach to correlation-based tensor analysis. This correlation-based metric outperforms Euclidean distance, and CTA proved better in its category.

For the Sri Lankan currency, Gunaratna and teammates developed an ANN-based currency recognition system [48]. They used grayscale compression to minimize the false rejection of currency SL Rupee notes. A special linear transformation is used to de-noise the currency notes without losing vital currency features. This transformation performs the mapping between the original grayscale and smaller grayscale range of 0 to 125. After de-noising and transformation, edge detection algorithm is applied to identify old and new currency notes properly. In the end, a three-layer ANN is used to classify the notes, and the currency is identified.

Jianbiao He et al., in 2008 [50], designed an ARM and uClinux based system to recognize the currency notes. For data acquisition at real-time processing, uClinux was not capable enough, and hence RTLinux was introduced later for the same. A real-time control layer was added to handle the real-time hardware level interrupts. In this, the data acquisition is performed by the kernel as a high priority task at the control layer. By this, they improved the data acquisition for paper-based currency identification.

In designing of assistive device for blind in currency recognition, Remi Parlour and group used bio-inspired image analysis software to identify the denomination of the currency. They used a real-time object identification system to increase the reliability of the system. The system prototype has been tested for daily use by the blind people and found reliable [51].

Wang and Lin used preprocessing techniques like Edge detection, segmentation, Color detection, binarization of images, Gaussian blur and Histogram equalization to identify the images [53].

For recognition of eroded currency notes, Fatemeh Daraee developed an algorithm using wavelet transform for Farsi currency [54]. Here, the front and back sides are extracted using face-detection algorithm. Later, the central part of the currency, containing the texture, is extracted and in this region, the wavelet transform is applied to extract the features of the currency. With these features, using a classifier, the denomination is decided, and it is proved to be 80% accurate while testing.

For image clustering, Sun Xu et al. proposed K-means based ACO on addressing the issue of inaccurate classification of K-means and slow convergence of ACO [55]. In this, they use K-means results as input to ACO along with illumination probability and pixels to find the appropriate nodes to cluster the images. Through testing, they proved that it improves classification accuracy by adjusting misclassification of K-means and also improves convergence speed.

Debnath et al. presented a currency recognition system using Ensemble Neural Network. (ENN) Here, a negative correlation is used to improve the accuracy in identifying the individual parts in an ensemble of the captured image. The individual neural networks are trained in ENN using negative correlation only. Since the currency in the marked could be old or new and tempered too. So, first, the captured image is converted into grayscale and compressed in the desired scale. After this, each pixel of such a compressed image is given as an input to the ENN. It has been tested and proved that the system could recognize currency which is highly noisy and old. Here, ENN is used to classify the currency into the appropriate denomination. The system is developed for Bangladeshi Taka [56].

Using Local Binary Pattern (LBP), Junfang Guo proposed a block-LBP algorithm to extract characteristics of a Chinese currency image [57]. In this, they decomposed the image into M X N blocks. The LBP value of every pixel is calculated, and a histogram is generated which is called block-histogram. The block-histogram is then normalized, and image features are extracted. The verification is done by comparing it with the templates to improve the reliability.

To identify the numbers written on the paper money, Ke-Yong Shao et al. developed a method to prevent illegal trade [59]. From pretreatment of the pay per currency to identifying the digits on the note, they went through the profound process. They developed the identification method based on a change in the intersection between the digit character and horizontal line or arc. In the method, the distance between two points from left to right side is calculated upon a change in the line of intersection and compared with a threshold value to determine if there is an arc or not? Here, the local difference value is confirmed through programming and highly adaptable. When classification features are less, the computing will be low, and hence identification is quick and accurate up to 97.5%.

Chi-Yuan Yeh and his teammates gave a method to identify the counterfeit notes using multiple kernel support vector machines to minimize false rate. Here, each banknote is divided into partitions and for each partition; the luminance histogram is created and taken as input to the system. Each partition is mapped with a kernel, and then all the kernels are combined using linear weights into a matrix. Optimal weights with kernel matrices are obtained using semi-definite programming. Here, only non-negative kernels weights are considered along with the sum of the weights set to the unity to achieve computational efficiency in terms of time and space. The method is proved as the best in its category of SVM based counterfeit currency identifier [60].

Feature matching is an important phase in image classification. To do that, finding distinguishable features from the scene is a vital part and foremost thing to be done. Scale Invariant Feature Transform (SIFT), developed by David Lowe, was the most widely used feature detection algorithm since its inception in 1999 [16]. The algorithm was developed to keep the image features intact on rotation, scaling, translation or any other transformation operation. David used stage filtering to detect features in the images. Using low residual least-squares, the final verification of key features was done. He showed that from cluttered or occluded images, even, the features are detected in less than 2 seconds. After a few years, in 2006, Edward and Tom proposed a new algorithm, named, Features from Accelerated Segment Test (FAST) [32]. They found that Harris or SIFT cannot work at the full frame rate. They also noted that if the same scene is viewed with a different viewpoint, then it should give the same set of features. Through experiments, they found that they intended to accelerate the speed of feature detection, yet the algorithm beats other feature detector algorithms except for the presence of noise. After two years of FAST, Speeded Up Robust Features (SURF) [49] was introduced Herbert and his team. It outperforms all previous feature detector algorithms in terms of speed and robustness. They used image convolutions and combined two Hessian matrix-based and distribution-based feature detectors. Michael and his colleagues, in 2010, developed another image feature detector [52]. They named it as Binary Robust Independent Elementary Features (BRIEF). In their work, they used Hamming distance for finding similarities in images instead of L2 distance. The algorithm is proved to be better than SURF in time and recognition, both. In 2011, the OpenCV team, Ethan et al.

gave an alternative to all these feature detectors and developed Oriented FAST & Rotated BRIEF (ORB) which is more robust and faster [61]. It can be used for 3D image reconstruction. They used the strength of both the algorithms FAST and BRIEF to improve the feature detection. It is proved that ORB is faster than SIFT by order of 2. The biggest benefit of using ORB is, it is open source and free to use as compared to SIFT and SURF. The SIFT and SURF are patented algorithms.

In their work for banknote recognition [62], Hasanuzzaman and group at CUNY proposed a component-based framework using Speeded Up Robust Features (SURF). They proved that SURF is better in collecting and analyzing class-specific information and adaptable to viewpoint changes. Along with this, SURF handles noise, image rotation, scaling and illumination changes and proved 100% effectiveness on the tested dataset.

Abhishek Verma developed a new color image descriptor for image searching named oRGB-SIFT by combining oRGB color space and power of SIFT [64]. He integrated it with color SIFT, grayscale SIFT, PHOG (Pyramid of Histogram of Gradients) and LBP (Local Binary Patterns). For image classification, he used the Enhanced Fisher Model and K Nearest Neighbor. The work was tested using the Iris Challenge Evaluation database to show performance improvement.

For visually impaired people, Nektarios et al. developed a currency recognition system for mobile phones. They used SIFT for finding key points and k-means for image clustering. The algorithm is designed to take care in terms of memory and speed both [65].

Kwang-Kyu used ACO based image classification to retrieve images from the cloud in [66]. He used simple ACO for feature extraction, and these features are verified using reduced feature subset. Upon best feature found, it is returned as a label for the image. Here, the population of ants and intensity of pheromone of any feature are the crucial parameters. In a similar attempt of ant-based classification [67], Rebika et al. used swarm intelligence to classify the images.

In the early 2020s, deep convolution network started gaining momentum. In the same direction, Alex and his colleagues trained large convolution network with approximately 1.2 million images with 1000 different classes. They formed a neural network of around 60 million parameters and 650,000 neurons with five convolution layers. These layers are followed by max-pooling layers and fully connected layers which finally labels the images. In this attempt, they reduced the error rate from 37.5% to 15.3% [68].

For Persian banknotes recognition, F Poorahangaryan et al. developed a wavelet and ANN based algorithm [69]. In these banknotes, images are captured using the scanner, and they are converted into grayscale images first. On this, the discrete wavelet transform is applied on it to extract the features of the currency notes. At the end, a multilevel artificial neural network is used to classify the currency in one of the eight classes of denominations. The algorithm is proved 99.12% accurate upon tested on 320 samples of Persian notes.

To identify the Mexican banknotes with their color and texture features, Farid, Jair, and Asdrubal, used artificial vision. For color, they used RGB space, and for texture features, they used the Local Binary Pattern (LBP) [70]. They also used Wiener pre-processing filter to de-noise the currency notes. The currency recognizer proved to be effective on severely worn, torn and mistreated notes.

Sugata, Abhishek, and Liu developed four novel color descriptors based on local binary patterns. They used their previous work of oRGB color palette with LBP and PHOG. For testing purpose, they used KTH-TIPS2-b and MIT scene database [77].

Bolun Chen et al. made a successful attempt to use Ant Colony Optimization for feature selection using directed graphs with a complexity of O(2n) [79]. They tested it with two large image datasets and several non-image datasets too to show improvements in image labeling.

To improve the performance of the currency recognition systems, Shan Gai et al. gave a new feature extraction method using Quaternion Wavelet Transform [80]. It gives one shift invariant and three other phases based on the applied algorithm arithmetic. Here, the Generalized Gaussian Density (GGD) is applied to capture the statistical characteristics of coefficients generated by QWT. In the end, the neural network is used as a classifier to denominate the banknote. The authors tested the algorithm and are having a higher recognition rate.

Cerna et al. used Bag of features and Histogram of Gradients (HOG) to develop a face detection algorithm [81]. HOG has been proved better descriptors for feature detection. They have been proved better especially for face detection in a situation of occlusion and illumination variations. The accuracy of correct labeling was found to be 89%.

In [83] their work for Pakistani currency recognition, Ali and Manzoor proposed a method by selecting an appropriate feature of the currency. In the process, the captured image of the currency is preprocessed using grayscale conversion, de-noising, and binary conversion. During feature extraction, various features like Euler number, area, height, width, aspect ratio, etc. are extracted from the captured image. Here, MAT file is used the store image features extracted and are used for the classification purpose to identify the currency accurately.

In [84], L Tu and C Dong write that the feature detectors have better stability over scale and illumination conditions of images. However, the area that has been covered during image capture also affects the feature detection. They experimentally proved that histogram equalization might improve the results in feature matching using SIFT and ASIFT.

In an attempt to evaluate the performance of ORB, Yu-Doo et al. extensively tested and analyzed the SIFT, SURF against ORB. They proved that ORB is far better in terms of time but performs badly than the others [88].

Hongli Yu and Yingyong Zou developed a money number identification system to quickly identify the numbers on the currency notes [89]. They used gray value accumulation for quick positioning and edge detection to get the ROI using the least square method. In addition to this, geometrical rotation and adjacent gray interpolation are also used. Using characteristics of character structures, imaginary line and point of intersection feature a recognition judgment tree is created to recognize the character. It is proved as highly accurate during the simulation.

With a non-parametric approach, Anas gave a novel approach for paper-based currency recognition [90]. They created the non-parametric model by averaging Region of Interests (ROI) of all the banknotes. They also made provision for unknown banknotes by calculating coefficients of determinations to distinguish it from known banknotes.

Muhammad Sarfaraz, in his work [91], developed an intelligent system for currency recognition based on interesting features and the correlation between images. For classification purpose, here, Radial Bases Function Network is used. The system was tested for 110 Saudi Arabian currency with all possible test cases as worn, torn, tilted notes, etc. and found 91.51% accurate. He further improved the accuracy with 99.09% average recognition rate using feature detection and weighted Euclidean distance for classification [92].

In [93], another attempt to compare the performance of the feature detectors and descriptors, Antti et al. used Caltech and ImageNet database of images. They made the comparison with various combinations of feature detectors and descriptors. It was found that original SIFT is best among its categories and dense sampling is far better than key points detectors.

Tuyen Danh Pham et al. developed a system to recognize the currency, fake or real, and denominate using one-dimensional line image sensor [94]. Here, only visible light is used to identify the soiled, creased, torn or worn note. The classification of the currency is done using features extracted from the region of interest (ROI) containing little texture. A 1-level discrete wavelet transform is used to differentiate between a real and fake note. Later, the optimum DWT features representing the real and fake note are obtained based on linear regression with data measured by a densitometer. The features are given as input to the SVM classifier to identify the denomination of the currency. They improved the work with more discriminating regions using similarity mapping [108].

Martin Abadi and his group at Google Research lab developed TensorFlow technology for machine learning [101]. It is an interface for machine learning implementation for distributed and heterogeneous environments. It has a wide variety of applications ranging from information retrieval, video and image processing, robotics, GIS, NLP, etc.

The first version of TensorFlow was officially released in late 2015 under Apache license. With the TensorFlow framework, Karen and Andrew developed a large-scale image recognition system using a convolution neural network with 19 convolution layers. They used ILSVRC-2012 image dataset of 1.3 million images for training and 100000 images for testing [102].

For new and used banknotes' recognition, Chao Tong et al. developed a five-layered parametric classifier [103]. It uses feature points in grayscale images, grayscale gradients and a DAG-SVM classifier with 98% accuracy.

For object detection and image classification, Druzhkov and Kustikova analyzed deep learning techniques and tools available [104]. They tested DeepLearn Toolbox, Theano, Pylearn, Deepnet, Deepmat, Darch, Torch, Caffe, nnForge, CXXNET, Cudaconvnet, CudaCNN, EBLearn, Hebel, Crino, Lush and R-CNN.

For Ethiopian currency, Jegnaw and Yaregal made a two stage recognition process. Categorization stage is responsible for denomination recognition, and verification stage is responsible for checking if the currency is real or fake. The accuracy of the system is found to be 90.42% and 83.3% for genuine and fake currencies respectively [105].

Qiqi and team used a bag of visual words for spatial image classification using local and global features of images [106]. For feature detection, they used SIFT and tested it on UC Merced and Google datasets with an accuracy of 96.88%.

To compare SIFT, KAZE, AKAZE, and ORB, Oskar and Steffany proved that SIFT is still the best feature detector in its categories [107]. Though run-time performance in terms of time it takes to detect the features is quite large concerning ORB. The ORB outperforms all other algorithms in terms of time, but at the same time, it performs worst in terms of accuracy with an average value of 52.5%.

Frazer made a comparison of Open CV feature detectors SURF, Brute Force and BRISK with Brute Force [109]. He concluded that if a number of features detected are more important than SURF is better. He also proved that BRISK and Brute Force combined performs better when some features matched are more important. He proved here that the ORB finds the least number of features in its category.

Li, Xi, and Li used deep convolution network for reconstruction of the hyperspectral image using neural network classification [110]. They proposed a hyperspectral imagery model using deep convolution network for feature enhancement. CNN trains these data, and efficient extreme learning machine reconstructs the images using the classification approach.

Matthew used a bag of words and developed a new COSFIRE descriptor using trainable COSFIRE filter for keypoint detection and recognition of images. This descriptor is combined with a bag of words and evaluated against SIFT and BRISK giving higher accuracy for unseen images of different categories [111].

M Hassaballah writes about basic concepts of image comparison like feature detectors, descriptors, key points, feature extraction and matching [112].

Google Brain team worked on TensorFlow for large-scale machine learning applications. They showed that TensorFlow gives an unbelievable performance for many real-world applications and libraries like Caffe, Neon, and Torch with Inception-v3 model [113].

Lee, Hong, Kim, and Park made an exhaustive survey of various banknote recognition methods across the world [114]. It talks about all four major areas of research for banknote recognition namely denomination identification, fake note recognition, and serial number recognition and note fitness decision. They detailed every aspect and provided an in-depth analysis of problems faced in techniques and directions for further research.

In their work of spatial image classification using a bag of visual words (BoVW), Fend, Liu and Wu used CNN for optimization of image features and uses BoVW as a tool to identify the images in the scene and achieved 90.1% accuracy [115].

Rawat and Wang carried out a detailed analysis of deep convolution neural network for image labeling. They carried out it using classification benchmark datasets like MNIST, Caltech, NORB, CIFAR, ILSVRC, etc. They noted that starting from 2010 ILSVRC image classification has topped, latest with a CNN of 152 layers [116].

For large-scale image classification, Yu et al. gave a novel way of learning using multitask sparse metrics hierarchically [117]. The tree learns by learning over sibling nodes and transfers learning specific metric to its sibling child nodes to learn more specific distinguishable metrics. They demonstrated that their algorithm could perform better than the other traditional algorithms for large-scale images.

To classify the remote sensing images, Wang et al. designed an SVM and binary coded ACO based algorithm (BACO) [118]. The performance of SVM depends on high-dimensional features, and remote sensing images contain such features. So dimensionality reduction can highly impact the accuracy and working of the algorithm. They took care of this by using binary coded Ant Colony Optimization method for feature selection and SVM parameters. They proved that combined SVM and BACO perform better for remote sensing images.

For performance comparison of SIFT, SURF, and ORB, Ebrahim, Siva, and Mohamed used distorted images in [119] their work. They showed that for different conditions of images, all the algorithms perform differently. But, they also showed that the average performance of the ORB comes out to be 51.95% only, which is the least among all the feature detectors.

Iyad and Sahar made a comparison between color SIFT and grayscale SIFT for currency recognition on mobile devices [120]. They showed that color SIFT approach performs much better than the other one regarding time and classification accuracy.

Andrew and his team at Google developed a CNN named MobileNet for mobile vision applications. They used Inception-v3 model of TensorFlow and tested on various image datasets with accuracy ranging from 72% to 89% [121].

Dittimi, Hmood, and Suen proposed a new approach of banknote recognition using HOG and Multi-class SVM with efficient error correction [122]. It identifies the banknote with any side or part visible of a denomination. They tested it for Canadian Dollar, US Dollar, and EURO currencies.

2.2 WORK CARRIED OUT FOR THE INDIAN CURRENCY

Since our work is concentrated on Indian currency recognition only, so this section discusses the work carried out in the context of the Indian currency.

The recognition system developed by Gopal Krishan is consists of two parts [58]. The first part performs preprocessing, including edge detection, data compression to reduce the dimensionality, and extracting features. The second phase performs the actual recognition, in which the core is a neural network classifier. For number recognition, the algorithm lets the computer understand the numbers and views them according to the computer process. He proposed a new technique for extracting serial numbers of Indian paper currency which can be used for recognition or database purpose using the MATLAB image processing toolbox. He proved that the proposed technique could be used further in recognizing the currency notes with the help of neural network methods.

In their work [63], Trupti et al. presented the Embedded System for checking if the currency is counterfeit or not. It is designed for all types of Indian currency denominations. It works on a specific feature of the Indian currency which is not easily imitable for a pretty long time. It consists of mainly three components. The currency image is first preprocessed by reducing dimensionalities, and its features are extracted. Feature extraction is done according to the HSV (Hue, Saturation, Value) color space. In the next step, the currency is recognized using a neural network classifier, and the result is displayed on AVR microcontroller ATMega32. The microcontroller then determines the validity of the note by glowing LED for Counterfeit Paper Currency. It is claimed that the success-rate of the counterfeit detection with is 100%.

To make the currency identification more robust, Chetan and Vijaya gave an approach of side invariant recognition [71]. Along with LBP, Gabor Wavelet transform and image subtraction, the used template matching technique for finding the match for image identification.

To deal with fake currency problem, Sanjana and her colleagues proposed an automated recognition of currency notes using feature extraction, classification based in SVM, Neural Network and heuristic approach [72]. Here, the machine is fitted with a CDD camera which scans the image of the currency note considering the dimensions of the banknote and the program processes the image segments using SVM classifier and character recognition methods. An artificial NN is also used to train the data and classify the segments using the respective datasets.

Rubeena proposed a system with an approach for verification of Indian currency banknotes [73]. The currency is verified using image processing techniques. It consists of some components including image processing, edge detection, image segmentation, characteristic extraction, comparing images. These approached used to detect the features of paper currency. The final result tells if the currency is genuine or counterfeit.

Hanish and P Kumar in [74] showed that every five seconds, a person in the world goes blind. The blind people have a reduced perception of the world around them and thus face a lot of difficulty in carrying out their day to day tasks. The Indian currency notes of different size are having just ten mm between two consecutive denominations. This makes it highly difficult for a blind person to recognize its denomination correctly. They developed an efficient currency note localization algorithm that localizes currency notes in color images. They are fed into the recognition module for determination of the denomination of currency note.

Rushabh Bhandari, in his attempt to make Indian currency recognition system, developed a java based application to run on Android OS platform. In this, an image is captured of the currency note and converted into grayscale. After this, the image is applied to linear transformation and edge detection algorithm later. The detected horizontal edges are given as input to the 3-layer back propagation network for classification of the currency [75].

In their work [76], Bhawani et al. used the LBP algorithm using Neural Network to simplify the process of recognition with high speed. The experimental results show that the LBP method has a high recognition rate. It is showed that the recognition ratio is 100% in the case of good quality images.

Jain and Ritu in [82] their work, use extracted ROI with Pattern Recognition and Neural Networks matching technique for currency recognition. First, they acquire the image by the simple flat scanner on fix dpi with a particular size and then applies some filters to extract the denomination value of the note. They use different pixel levels in different denomination notes. Mainly, the Pattern Recognition and Neural Networks are used to match or find currency value/denomination of paper currency.

Binod and his teammates in [85] gave an approach to detecting fake currency notes automatically using feature extraction with HSV color space and other applications of image processing. They implemented a fake note detection unit with the MATLAB algorithm.

Ajith in his work used a 3×3 grid for currency recognition [86]. Based on geometrical shape, the denomination of currency such as 100, 500, 1000 is determined with the help of Neural Network Classifier. They experimented extensively large dataset and demonstrated the efficiency of the approach.

Suriya et al. in [87], presented an application for recognizing currency notes using computer vision techniques which can run on a low configuration smartphone. The application runs on the device without the need for any remote server. Their method is a generic and scalable to multiple domains apart from the currency bills. In their work, they used a visual Bag of Words (BoW) based method for recognition. To make the algorithm robust, they first segment the notes from the background using an algorithm based on iterative graph cuts. They formulate the recognition problem as an instance retrieval task. They demonstrated and evaluated the performance on a set of images captured in diverse natural environments, and report an accuracy of 96.7% on 2584 images.

Komal and her teammates proposed a method to recognize the Indian currency using frequency domain feature extraction [95]. It uses local spatial features of a currency image. The captured image is preprocessed for the application of 2D discrete wavelet transform. Statistical moments are extracted from the approximate efficient matrix, and a set is made of coefficients. These extracted features are used for classification and recognition of the currency.

In [96], Manikandan and Sumithra use Gaussian mixture model, Texture-based recognition and Neural networks for currency recognition. The system proposes the technique for extracting the denomination of Indian currency note which can be used the localization algorithm that localizes currency notes and color matching technique used to identify the currency note. In that, they perform preprocessing, including detecting edges, compressing data dimensionalities, and extracting features and recognize the denomination with the help of SIFT feature extraction. In this, they proved that the system accuracy is of 93% on 165 images.

Kavya and Devendran, in [97], designed a system that helps in the identification of Indian currency notes and to check if it is fake or genuine. They used currency features such as See Through register, See Through register symbol or Identification mark, Security thread, Governer's signature, Microlettering, year of print, etc. These features are segmented using a 3x3 grid with SIFT technique for efficient matching of the features.

To provide counterfeit currency detection, Prasanthi and Setty used Sobel operator with gradient magnitude along with basic preprocessing techniques. They used the security feature detection during identification of currencies [98].

Savitha and Ramya, with an intention to assist visually impaired people, developed an algorithm to detect food, clothing, traffic signals with intra-class variation. For this, they used Radon Signature descriptor for global cloth, food, and signal patterns. They claimed 92.55% accuracy of their algorithm [99].

In [100], Amulya and Hari gave a robust framework for Indian currency note recognition which effectively recognizes the various Indian currency denominations. The system firstly preprocess the image of currency notes acquired by a digital camera and then extract and analyze three unique features of each denomination. Based on the unique and discriminating features, they classify and recognize the currency notes. The success rate of the counterfeit detection with the properly captured image is 100%.

Following table 2.1 summarizes the work carried out exclusively for currency recognition across the world, including Indian currency.

Sr. No.	Currency Recognition Approach	Currency	Accuracy	Year
1	Neural Network [3]	USD	98.08	1993
2	Neural Network, Optimized Mask and Genetic Algorithm [5]	USD	>95%	1995
3	Hybrid Neural Network [6]	USD & Japanese	92	1996
4	Multilayered Perceptrons in NN [7]	USD		1996
5	Neural NN with Gaussian Distribution [14]	USD, CA$, AU$, Krone, Franc, GBP, Mark, Pesetas	High	1998
6	Neural NN and axis-symmetrical mask [18]	Euro	97	2000
7	Neural NN and Principal Component Analysis [21][24]	USD	95	2002
8	Back Propagation NN [26]	Chinese Renminbi	96.6	2003
9	Markov Models [40]	USD, Euro, Dirham, Rial	95	2007
10	Ada-Boost Classification [45]	USD	High	2008
11	Neural Network [46]	Malaysian Ringgit	High	2008
12	Artificial Neural Network [48]	SL Rupee	High	2008
13	Data Acquisition [50]	Chinese Renminbi	100	2008
14	Bio-inspired Image Processing [51]	Euro	100	2009
15	Image Processing [53]	Chinese Renminbi & Swiss Kronor	High	2010
16	Wavelet Transform [54]	Rials	81	2010
17	Ensemble Neural Network with Negative Correlation Learning [56]	Bangladeshi Taka	98	2010
18	Local Binary Patterns [57]	Chinese Renminbi	100	2010
19	Image Processing & Neural Network [58]	Indian Rupee	High	2010
20	Intersection Change [59]	Chinese Renminbi	97.5	2010
21	Support Vector Machine [60]	Chinese Renminbi	87.097	2011
22	Component-based framework using SURF [62]	USD	100	2012
23	SIFT and K-means clustering [65]	USD	100	2012
24	Wavelet Transform & Neural Network [69]	Dirham	99.12	2012
25	Local Binary Patterns and RGB Space [70]	Mexican	97.5	2012

26	LBP, Gabour Wavelet Transform, Image subtraction [71]	Indian Rupee	High	2012
27	SVM, Neural Network and Heuristic [72]	Indian Rupee	High	2012
28	Edge detection, segmentation, feature extraction [73]	Indian Rupee	High	2012
29	Localization using the color of images [74]	Indian Rupee	High	2012
30	Grayscale, linear transformation and edge-detection, 3-layer neural network [75]	Indian Rupee	High	2012
31	LBP and neural network [76]	Indian Rupee	High	2012
32	LBP and color descriptors [77]	Indian Rupee	High	2012
33	Discriminative color [78]	Mexican	High	2013
34	Quaternion Wavelet Transform & Generalized Gaussian Density [80]	USD, Renminbi, and Euro	99.68	2013
35	ROI, Pattern Recognition and Neural Network [82]	Indian Rupee	High	2013
36	Basic Feature Extraction using Euler Numbers [83]	Pakistani Rupee	High	2013
37	Feature extraction using HSV [85]	Indian Rupee	High	2014
38	3X3 grid and neural network [86]	Indian Rupee	High	2014
39	Bag of words [87]	Indian Rupee	96.7	2014
40	Number Recognition [89]	Chinese Renminbi	95.92	2014
41	Instance Retrieval and Indexing [87]	Indian Rupee	96.7	2014
42	Non parametric approach [90]	Saudi Arabia Rial	High	2015
43	Radial Basis Kenrel Function [91][92]	Dirham	91.51	2015
44	2D discrete wavelet transform, Frequency domain extraction [95]	Indian Rupee	High	2015
45	Gaussian mixture model, texture and neural network [96]	Indian Rupee	High	2015
46	See-through register, thread and identification mark [97]	Indian Rupee	High	2015
47	Sobel operator with gradient magnitude [98]	Indian Rupee	High	2015
48	Segmentation, feature extraction [100]	Indian Rupee	High	2015
49	Categorization and verification [105]	Ethiopian	90.42	2015
50	The region of Interest (ROI), Discrete Wavelet Transform, Linear Regression and SVM [94][108]	Indian Rupee	High	2015
51	Color SIFT and Grayscale SIFT [120]	Jordanian Currency	High	2017
52	HOG and Multiclass SVM [122]	USD, CA$, Euro	High	2017

Table 2.1 Summary of Currency recognition work across the world

2.3 CURRENCY RECOGNITION TOOLS/APPS

The following text discusses tools, and Mobile Apps developed so far for currency recognition in different countries.

Maverick Money Reader [124] is an application developed by Jesse Saitoo and his supervisor Dr. Akash Pooransingh to enable visually impaired people to identify the currency of Trinidad and Tobago. It is an automatic money detector developed at the University of West Indies.

Money Reader developed by Bishoy Gamal for the currency recognition for the blind and visually impaired people to detect the American Currency. In this, the user has to place the currency in front of the camera, and the rest of the things are processed by the system automatically. It has around the accuracy of nearly to 95%. (Play store).

MoneySpeaker [125] is a mobile application developed by the Human-Machine Interaction Lab and Computer Science Dept. at the University of Engineering and Technology, Vietnam National University, Hanoi. This app helps visually impaired people to identify Vietnamese banknotes (Play store).

Smart Saudi Currency Recognizer (SSCR) is a smart android application that helps the blind community to handle cash matters efficiently by resolving issues related with Saudi currency recognition being faced by people (Play store) [126].

TalkingMoney is a Money Reader Application and dedicated for the Visual impaired people. It is an Android App, and blind people can use their smartphones to recognize the value of paper banknotes. Currently, the application is working for Egypt currency (Play store).

EyeNote [127] is a free mobile device application to identify denominations of Federal Reserve Notes (US paper currency) as an aid for the blind or visually impaired.

LookTel Money Reader instantly recognizes the currency and speaks the denomination, enabling people experiencing visual impairments or blindness to quickly and easily identify and count the number of currencies of many countries [128].

In the US, all the denominations are of the same size making it difficult for blind people to identify the correct denomination from another. In such situation, the Governments have provided a way to help them to tell apart the different money denominations. In countries like Australia and Malaysia, every denomination is of distinct width and length making the identification easier for the blind people. In Canada, the currencies have the provision of Braille dots representing a specific denomination. Blind people can easily read that Braille dots and know the amount denomination they are holding. In India, the RBI has introduced an embossed pattern for every currency note. The problem with this embossing is as the currency gets older, the embossed spot gets faded. Apart from these, the blind people themselves use their ways like Folding Money, A Wallet with Many Dividers, Scanners, and Assistive Technology, etc. to identify money. Though the use of scanners or any other assistive aid is an effective way to identify money, it is only possible when you are at home or if such devices are handy [129].

Having discussed about all the research works across the world, in India and the available Apps/Tools, it is concluded that the research works that have been proposed, mainly for Indian currencies, are not materialized using some standard algorithms in the form a tool or app in market that can help the blind people to identify the Indian currency in their regional languages. Apart from the proposed research works, in India, the real implementations of currency recognition tools are limited to the ATMs and Banks only, which are neither affordable nor handy to a common man! Looking towards a need of a standard algorithm(s) and a tool that can help the blind people in India to recognize the Indian currencies in their mother tongue (regional languages), this work has been carried out with a noble intention.

2.4 TOOLS USED

2.4.1 The OpenCV

Open Computer Vision library developed in C++ by Intel. It contains more than 2500 optimized algorithms for image processing and computer vision applications. It supports C, C++, Java, Python, etc. languages and Android, iOS, Windows, Linux platforms. It contains the following modules:

1. Core: This module defines basic data structures, including the dense multi-dimensional array *Mat* and basic functions used by all other modules.
2. Imgproc – It is an image processing module that includes linear and non-linear image filtering, geometrical image transformations (resize, affine and perspective warping, and generic table-based remapping), color space conversion, histograms and many more functionalities.

3. highgui – For UI based applications, this module provides functionalities for user interface creation.
4. gpu - GPU-accelerated algorithms of open CV are available in this module.
5. ml - machine learning classes used for statistical classification, regression, and clustering of data are available in this module
6. objdetect – This module contains functionalities for objects detections like faces, eyes, mugs, chairs, etc.
7. video – This module provides functionalities of motion estimation, background subtraction, and object tracking algorithms for video processing and streaming applications.
8. calib3d – This module provides 3d related functionalities. For example, multiple-view geometry algorithms, single and stereo camera calibration, object pose estimation, stereo correspondence algorithms, and elements of 3D reconstruction.
9. features2d – All image feature detectors and descriptors are available in this module.
10. Video I/O – This is an easy-to-use interface to video capturing and video codecs.

The following figure shows the openCV spectrum supporting wide variety of Platforms, Programming Frameworks, etc.

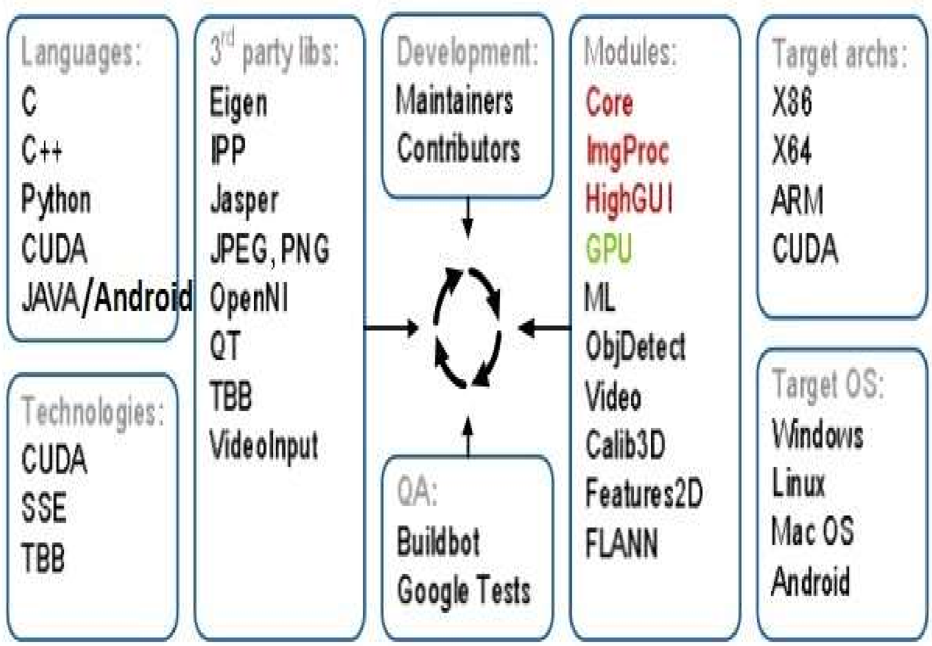

Figure 2.1. The OpenCV spectrum

Apart from these, there are other modules like FLANN and Google test wrappers; Python bindings are also available. In spite of being developed in C++, the automatic memory management makes it more powerful. Other features like auto-allocation of output data, limited pixel types, error handling and multi-threading capabilities make it more versatile to use.

2.4.2 Android

Released in 2008, Android is the mobile operating system developed by modifying the Linux kernel by Google. It is mainly used for smartphones and handheld devices. Starting from Alpha and Beta, Android versions, later, started being named with the name of desserts. For development, JetBrains has developed Android Studio. The latest version of Android is Oreo, released in December 2017. The following figure represents the Android versions released till date.

Figure 2.2. Android versions, December 2017

2.4.3 Python

Python is an object-oriented, general purpose, interactive and a high-level programming language. It is also a *Programming language for everyone*! It was developed in the late 90s and has gained momentum recently, mainly, due to its applicability and versatility for machine learning applications. This has been used for machine learning programming. PyCharm is one of the IDEs available for python programming from JetBrains.

SUMMARY

This chapter, first, discussed the literature study in the area of image/object identification and classification. It also discussed the currency recognition work carried out for the Indian currencies. The third section briefly described the currency recognition tools, and Apps available and the final section briefed about the tools and technologies used for the implementation of this work. The next chapter briefly describes the research works carried out and a proposed preprocessing algorithm.