

Evaluation of Machine Learning Algorithms for the Detection of Fake Bank Currency

at

**Sathyabama Institute of Science and Technology
(DEEMED TO BE UNIVERSITY)**

Submitted in partial fulfillment of the requirements for the award of Bachelor
Engineering Degree in Computer Science and Engineering By

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SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY (DEEMED TO BE UNIVERSITY)

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BONAFIDE CERTIFICATE

This is to certify that this Professional Training Report is the bonafide work of **Gadipudi Sandeep (38110142), Jusak Praveen Sikharam(38110219)** who carried out the project entitled “**Evaluation of Machine Learning Algorithms for the Detection of Fake Bank Currency**” under our supervision from November 2021 to March 2022.

Internal Guide

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Head of the Department

Submitted for Viva voce Examination held on

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Internal Examiner

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DECLARATION

I, **Gadipudi Sandeep (38110142), Jusak Praveen Sikharam(38110219)** hereby declare that the project entitled “**Evaluation of Machine Learning Algorithms for the Detection of Fake Bank Currency**” done by me under the guidance of **Dr S Gowri** at **Sathyabama Institute of Science and Technology** is submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering.

DATE:

PLACE: CHENNAI

SIGNATURE OF THE CANDIDATE

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ABSTRACT:

The currency has a great meaning in everyday life. Thus currency recognition has gained a great interest for many researchers. The researchers have suggested diverse approaches to improve currency recognition. Based on strong literature survey, image processing can be considered as the most widespread and effective technique of currency recognition. This paper introduces some close related works of paper-currency recognition. This paper has explained a variety of different currency recognition systems. The applications have used the power of computing to differentiate between different types of currencies with the appropriate layer n. Choosing the proper feature would improve overall system performance. The main goal of this work is to compare previous papers and literatures through reviews these literatures and identify the advantages and disadvantage for each method in these literatures. The results were summarized in a comparison table that presented different ways of reviewing the technology used in image processing to distinguish currency papers.

Chapter 1

1. INTRODUCTION

Despite a decrease in the use of currency due to the recent growth in the use of electronic transactions, cash transactions remain very important in the global market. Banknotes are used to carry out financial activities. To continue with smooth cash transactions, entry of forged banknotes in circulation should be preserved. There has been a drastic increase in the rate of fake notes in the market. Fake money is an imitation of the genuine notes and is created illegally for various motives. These fake notes are created in all denominations which brings the financial market of the country to a low level. The various advancements in the field of scanners and copy machines have led the miscreants to create copies of banknotes. It is difficult for human-eye to recognize a fake note because they are created with great accuracy to look alike a genuine note. Security aspects of banknotes have to be considered and security features are to be introduced to mitigate fake currency. Hence, there is a dire need in banks and ATM machines to implement a system that classifies a note as genuine or fake. In the recent years, Soft computing techniques have been widely used to solve problems that are difficult to solve using conventional mathematical methods. Supervised learning techniques are widely used in classification problems. This paper evaluates supervised machine learning algorithms to classify genuine and fake notes, and compares algorithms on the basis of accuracy, sensitivity, and specificity. Consider someone wants to deposit money in the bank. The notes that are to be deposited are given to a human being to check for their authenticity. As the fake notes are prepared with precision, it is difficult to differentiate them from genuine ones. A recognition system must be installed to detect legitimacy of the note. The system should extract the features of the note using image processing techniques. These features will be given as input to the machine learning algorithm which will predict if the note is true or fake. Supervised machine learning techniques such as BPN and SVM were implemented. The dataset used to train these algorithms was collected by extracting features from banknote images. The dataset also classifies all the samples into a particular class i.e. genuine or forged. A comparative study of these techniques with respect to their accuracy, sensitivity, specificity and precision rate is shown.

Currently, the use of paper money remains one of the main options for the exchange of products and services. However, one of the remaining problems is the detection of counterfeit banknotes, which increasingly resemble originals, making it difficult for someone who is not an expert in the field to detect them. On the other hand, there are machines for detecting counterfeit banknote; however, these are often expensive, so the identification and retention of counterfeits ends up falling on financial and government entities, with minimal community involvement.

In order to solve this problem and to present alternative solutions, in the state-of-the-art, there are proposals based on classical computer vision techniques. For example, from histogram equalization, nearest neighbor interpolation, genetic algorithms and fuzzy systems. However, the main problem of this type of methods is its low capacity of generalization for new examples as well as its accuracy. Another group corresponds to those methods based on deep learning w ac(DL) using convolutional neural networks (CNNs), which have outperformed to the classic machine learning techniques

and humans too in classification tasks. Considering the current importance of the CNNs in the field of computer vision, there are some proposals in the area of banknote recognition and counterfeit detection. For example, transfer learning (TL) with Histograms of Oriented Gradients for Euro banknotes, a YOLO net for Mexican banknotes or custom CNN architectures for dollar, Jordanian dinar and Won Korean banknotes have been proposed. However, one of the main disadvantages of proposals using CNNs that focus on fake banknote recognition is that there is no clarity about which design strategy is more appropriate, either custom or by transfer learning. When using transfer learning-based networks, there are many types of patterns that the network has learned, but they are not specific to the current task. On the other hand, custom networks are trained with a much smaller dataset than the pre-trained networks, but they specifically learn the patterns of this type of classification task. Another shortcoming found in the literature is that the impact of the freezing point (FP) of the pre-trained network on the performance of the classifier has not been analysed. According to the above, the main contributions of this research are as follows:

- A methodology to identify the best freezing point in models by transfer learning, for three different types of architectures: sequential, residual and Inception is proposed.
- A custom model inspired in AlexNet that has faster inference times in an embedded system than models by transfer learning is proposed.
- A comparative study for the fake banknote recognition task between a custom model and several models obtained by transfer learning, in terms of accuracy and inference times is given. The rest of the paper is organized as follows. Section presents the background of Convolutional Neural Networks and transfer learning. Section shows the proposed system of image acquisition and the used dataset. Section explains the proposed methodology for selecting the freezing point in the design by transfer learning. Section presents the proposed custom model. Section shows the results of the research. Finally, Section summarizes the work.

- Fake Currency has always been an issue which has created a lot of problems in the market.
- The increasing technological advancements have made the possibility for creating more counterfeit currency which are circulated in the market which reduces the overall economy of the country.
- There are machines present at banks and other commercial areas to check the authenticity of the currencies.
- But a common man does not have access to such systems and hence a need for a software to detect fake currency arises, which can be used by common people.
- This proposed system uses Image Processing to detect whether the currency is genuine or counterfeit.
- The system is designed completely using Python programming language.
- It consists of the steps such as grayscale conversion, edge detection, segmentation, etc. which are performed using suitable methods.

Chapter 2

Literature review

2.1. Detection of Fake currency using Image Processing

Abstract:

The main objective of this project is fake currency detection using the image processing. Fake currency detection is a process of finding the forgery currency. After choose the image apply preprocessing. In pre-processing the image to be crop, smooth and adjust. Convert the image into gray color. After conversion apply the image segmentation. The features are extracting and reduce. Finally compare the image into original or forgery.

Introduction:

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled in the form of multidimensional systems. Digital image processing allows the use of much more complex algorithms, and hence, can offer both more sophisticated performance at simple tasks, and the implementation of methods which would be impossible by analog means. Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as superpixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. Image restoration is different from image enhancement in that the latter is designed to emphasize features of the image that make the image more pleasing to the observer, but not necessarily to produce realistic data from a scientific point of view. Image enhancement techniques (like contrast stretching or de-blurring by a nearest neighbor procedure) provided by "Imaging packages" use no a priori model of the process that created the image. With image enhancement noise can effectively be removed by sacrificing some resolution, but this is not acceptable in many applications. In a Fluorescence Microscope resolution in the z-direction is bad as it is. More advanced image processing techniques must be applied to recover the object. Counterfeit money is imitation currency produced without the legal sanction of the state or government. Producing or using counterfeit money is a form of fraud or forgery. Counterfeiting is almost as old as money itself. Plated copies have been found of Lydian coins which are thought to be among the first western coins. Before the introduction of paper money, the most prevalent method of counterfeiting involved mixing base metals with pure gold or silver. A form of counterfeiting is the production of documents by legitimate printers in response to fraudulent instructions.

Methodology:

Overall Algorithm:

- A. Image of paper currency will be acquired by simple scanner or digital camera.
- B. The image acquired is RGB image and then it will be converted into gray scale.
- C. Edge detection of the whole gray scale image will be performed.
- D. After detecting edges, the four characteristics of the paper currency will be cropped and segmented.
- E. After segmentation, the characteristics of the paper currency will be extracted.
- F. The characteristics of test image are compared with the original pre-stored image in the system.
- G. If it matches then the currency is genuine otherwise counterfeit.

Modules:

Image Acquisition:

The first stage of any vision system is the image acquisition stage. After the image has been obtained, various methods of processing can be applied to the image to perform the many different vision tasks. Performing image acquisition in image processing is always the first step in the workflow sequence because, without an image, no processing is possible. There are various ways to acquire image such as with the help of camera or scanner. Acquired image should retain all the features.

Pre-processing:

The main goal of the pre-processing to enhance the visual appearance of images and improve the manipulation of datasets. Pre-processing of image are those operations that are normally required prior to the main data analysis and extraction of information. Image preprocessing, also called image restoration, involves the correction of distortion, degradation, and noise introduced during the imaging process. Image pre-processing can significantly increase the reliability of an optical inspection. Several filter operations which intensify or reduce certain image details enable an easier or faster evaluation. Image Adjusting is done with the help of image interpolation. Interpolation is the technique mostly used for tasks such as zooming, rotating, shrinking, and for geometric corrections. Removing the noise is an important step when image processing is being performed. However noise may affect segmentation and pattern matching. When performing smoothing process on a pixel, the neighbor of the pixel is used to do some transforming. After that a new value of the pixel is created.

Gray Scale Conversion:

The image acquired is in RGB color. It is converted into gray scale because it carries only the intensity information which is easy to process instead of processing three components R (Red), G(Green), B(Blue). to take the RGB values for each pixel and make as output a single value reflecting the brightness of that pixel. One such approach is to take the average of the contribution from each channel: $(R+B+C)/3$. However, since the perceived brightness is often dominated by the green component, a different, more "humanoriented", method is to take a weighted average, e.g.: $0.3R + 0.59G + 0.11B$.

Edge Detection:

Edge detection is the name for a set of mathematical methods which aim at identifying points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities. The points at which image brightness changes sharply are typically organized into a set of curved line segments termed edges. The same problem of finding discontinuities in 1D signals is known as step detection and the problem of finding signal discontinuities over time is known as change detection. Edge detection is a fundamental tool in image processing, machine vision and computer vision, particularly in the areas of feature detection and feature extraction. Edge detection is an image processing technique for finding the boundaries of objects within images. It works by detecting discontinuities in brightness. Edge detection is used for image segmentation and data extraction in areas such as image processing, computer vision, and machine vision. Based on this one-dimensional analysis, the theory can be carried over to twodimensions as long as there is an accurate approximation to calculate the derivative of a two-dimensional image. The Sobel operator performs a 2-D spatial gradient measurement on an image. Typically it is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. The Sobel edge detector uses a pair of 3x3 convolution masks, one estimating the gradient in the x-direction (columns) and the other estimating the gradient in the y-direction (rows). A convolution mask is usually much smaller than the actual image. As a result, the mask is slid over the image, manipulating a square of pixels at a time.

Image Segmentation:

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as superpixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images.

Feature Extraction:

Feature extraction is a special form of dimensional reduction. When the input data to an algorithm is too large to be processed and it is suspected to be very redundant then the input data will be transformed into a reduced representation set of features. Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

Conclusion:

This project proposed fake currency detection using image processing. In image pre-processing the image was cropped, adjusted and smoothed. Then the image converted into gray scale. After conversion the edges are detected. In edge detection used the sobel operator. Next the image segmentation is applied. After segmentation the features are extracted. Finally compared and find the currency original or fake.

2.2 Analysis of Banknote Authentication System using Machine Learning Techniques

ABSTRACT

Banknotes are one of the most important assets of a country. Some miscreants introduce fake notes which bear a resemblance to original note to create discrepancies of the money in the financial market. It is difficult for humans to tell true and fake banknotes apart especially because they have a lot of similar features. Fake notes are created with precision, hence there is need for an efficient algorithm which accurately predicts whether a banknote is genuine or not. This paper proposes machine learning techniques to evaluate authentication of banknotes. Supervised learning algorithms such as Back propagation Neural Network (BPN) and Support Vector Machine (SVM) are used for differentiating genuine banknotes from fake ones. The study also shows the comparison of these algorithms in classification of banknotes.

INTRODUCTION

Despite a decrease in the use of currency due to the recent growth in the use of electronic transactions, cash transactions remain very important in the global market. Banknotes are used to carry out financial activities. To continue with smooth cash transactions, entry of forged banknotes in circulation should be preserved. There has been a drastic increase in the rate of fake notes in the market. Fake money is an imitation of the genuine notes and is created illegally for various motives. These fake notes are created in all denominations which brings the financial market of the country to a low level. The various advancements in the field of scanners and copy machines have led the miscreants to create copies of banknotes. It is difficult for human-eye to recognize a fake note because they are created with great accuracy to look alike a genuine note. Security aspects of banknotes have to be considered and security features are to be introduced to mitigate fake currency. Hence, there is a dire need in banks and ATM machines to implement a system that classifies a note as genuine or fake. In the recent years, Soft computing techniques have been widely used to solve problems that are difficult to solve using conventional mathematical methods. Supervised learning techniques are widely used in classification problems. This paper evaluates supervised machine learning algorithms to classify genuine and fake notes, and compares algorithms on the basis of accuracy, sensitivity, and specificity. Consider someone wants to deposit money in the bank. The notes that are to be deposited are given to a human being to check for their authenticity. As the fake notes are prepared with precision, it is difficult to differentiate them from genuine ones. A recognition system must be installed to detect legitimacy of the note. The system should extract the features of the note using image processing techniques. These features will be given as input to the machine learning algorithm which will predict if the note is true or fake. Supervised machine learning techniques such as BPN and SVM were implemented. The dataset used to train these algorithms was collected by extracting features from banknote images. The dataset also classifies all the samples into a particular class i.e. genuine or forged. A comparative study of these techniques with respect to their accuracy, sensitivity, specificity and precision rate is shown.

DATASET DESCRIPTION

The dataset used to train the models is taken from UCI machine learning repository. Data were extracted from genuine and counterfeit banknote images. The dataset has 1372 instances. There are 5 attributes out of which 4 are the features and one is the target attribute. The dataset contains a balanced ratio of both classes which is 55:45(genuine: counterfeit). The target class contains two values: 0 and 1 where 0 represents genuine note and 1 represents fake note.

SETUP

The supervised learning models have been implemented in GNU Octave by applying the hold-out method to the input data. The dataset used is divided into two subsets i.e. ratio of 80:20. The bigger subset is used for training the models and the smaller subset is used to test whether the models can predict the genuineness of note or not.

MACHINE LEARNING TECHNIQUES

Back Propagation Neural Network

BPN uses gradient descent to train the artificial neural network. This method is efficient in adjusting the weights in the network by comparing the desired output with the actual output and distributing the error back to the hidden layers. The difference in actual and expected output is used by the cost function to calculate the error. BPN works in two phases; propagation phase where the input is forwarded through the network to generate the output and error is calculated at the output, weight update phase where the weights in the network are updated according to the error to gain the desired output. A standard BPN consists of 3 layers namely an input layer to accept the input which is connected to the hidden layer which processes the input and the output layer which gives the result.

The BPN model implemented has 1 input layer having four neurons, one hidden layer having eight neurons and one output layer having two neurons that gives the classification result. represents the two-dimensional plot where 100 random data points are displayed. displays the hidden units to see what features they are capturing the data by visualizing what the neural network is learning.

Support Vector Machine

Support Vector Machines are supervised learning models that evaluate the data and recognize the patterns to classify the data. It creates a decision boundary to separate the two classes in the data. In SVM, each data item is plotted on the graph and then classification is performed to find the hyper plane that differentiates the two classes. SVM uses a kernel function that projects the data from a lower-dimensional space to a higher-dimensional space. This is done to make the non-linearly separable data into linearly separable.

Kernel functions are used in SVM as SVM does not perform well with huge datasets. For implementation purpose, linear kernel is used which is especially used for classification where there are a few features and the number of test cases is large. In the model, as the dataset has linearly separable data, the linear kernel finds the linear margin that separates the two regions in the graph. This decision boundary is chosen such that it is maximally far away from each data point. represents the data that is

visualized on the 2-D plot. represents the classification of the dataset by the hyper plane that linearly separates the data.

RESULT AND ANALYSIS

Performance Measure

Following measures have been used to measure the performance of the models implemented

□

Accuracy – The accuracy of the test is its ability to differentiate the genuine and fake note test cases correctly.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

□

Sensitivity - The sensitivity of a test is its ability to determine the genuine note cases correctly.

$$\text{Sensitivity} = TP / (TP + FN)$$

□

Specificity - The specificity of a test is its ability to determine the fake note cases correctly.

$$\text{Specificity} = TN / (TN + FP)$$

□

Precision - The precision of a test is its ability to determine the number of notes that classifier labeled as genuine is actually genuine $\text{Precision} = TP / (TP + FP)$

Where,

True Positive (TP) = the number of cases correctly identified as genuine notes.

True negative (TN) = the number of cases correctly identified as fake notes.

False positive (FP) = the number of cases incorrectly identified as genuine notes.

False negative (FN) = the number of cases incorrectly identified as fake notes.

CONCLUSION

After analyzing various techniques used to detect forged banknotes, this paper presents banknote authentication for recognizing the banknote as genuine or fake by using two supervised learning techniques. Extensive experiments have been performed on banknotes dataset using both the models to find the best model suitable for classification of the notes. ROC and other metrics have been calculated to compare the performances of both the techniques. The result shows that back-propagation neural network outperforms support vector machine and gives 100% success rate. These techniques are an efficient way of solving the problem for all banking machines that accept all types of notes. In future, this work can be extended by categorizing the notes into different categories as Genuine, Low-Quality forgery, High-Quality forgery, Inappropriate ROI.

2.3. Currency Value Detection and Counting using Feature Extraction and Classification Algorithms

Abstract:

Image processing is the area in which currently many predictions are performed from the captured images. Currency Value detection aims at searching the features of the training dataset with the query image feature and obtains the respective value of the feature that has the match with query image. In present system the images are compared and matched according to pixel values and few features extracted, which consumes a lot of time for execution instead we can extract the desirable features that are used to identify and classify the type of image. The proposed technique aims to reduce the searching time of image retrieval and hence it improves the performance of image retrieval system using best suitable feature extraction algorithms offered by Matlab and instead of sticking to one feature extraction algorithm it is better to apply multiple feature extraction methods that improves the accuracy. To build an effective classifier it is better to add new components and new changes to the existing algorithms that increase the good impact on the classifier.

Introduction

Currency value detection is very useful and necessary in counting the notes and obtaining the total of the amount. It also helps the blind people to recognize the value of the note that they are holding just by scanning. If we configure the output with the text to voice converter the results can be heard by the blind. There has been lot of research and implementations for the Currency value detection. But the features extraction methods in image processing is also gaining its momentum. Efficient image database retrieval can be done only if we have a system that is able to automatically extract relevant features directly from the images stored in the database. But before implementing some classification algorithm it is very important to collect the currency of different nations and its values. It is also important to collect the relative values conversions from one type of currency to other to make the calculations more appropriate algorithm. To implement these algorithms we can use the R TOOL or MATLAB or JAVA or any programming language which does the basic functions, but if we use R TOOL or MATLAB the pre-processing gets easier as it has some pre defined functions which can be directly implemented. Once we get the dataset for training further we can proceed with feature extraction and classification algorithms. MATLAB provides many predefined packages for feature extraction like Local Feature Extraction, Feature Matching, Image Registration, Geometric Transformations. For currency value detection the best feature extraction method is to use Local Feature Extraction as it deals with the extraction of internal and interesting points to extract feature descriptors. Using such feature extraction methods will increase in accuracy and efficiency. For each feature extracted the corresponding class label is given and stored into the database. A classification algorithm is implemented to train the system with the available data so that it can classify the query image based on the features extracted. The implemented algorithm will detect the value of currency and applies the basic mathematical operations to find the total amount.

Methods and Procedures

In Local Feature Extraction there are many methods of detection of interesting points and extracting the features. SURF Feature extraction is one among them. The SURF algorithm alone may not be much efficient to make it more accurate we need to implement more than one feature extraction methods. As the currency detection is done basically by the number represented on the currency. So we can also implement the OCR (Optical character recognition) to recognize the numbers. To make it more efficient we can also take mean and standard deviation of neighbor pixel values to include a feature which deals with color of objects on currency.

Feature Extraction Methods

SURF Feature Extraction method: speeded up robust features (SURF) is a patented local feature detector and descriptor. It can be used for tasks such as object recognition, image registration, classification or 3D reconstruction. To detect interest points, SURF uses an integer approximation of the determinant of Hessian blob detector, which can be computed with 3 integer operations using a precomputed integral image. Its feature descriptor is based on the sum of the Haar wavelet response around the point of interest. These can also be computed with the aid of the integral image. SURF descriptors have been used to locate and recognize objects, people or faces, to reconstruct 3D scenes, to track objects and to extract points of interest.

The algorithm has three main parts: interest point detection, local neighborhood description and matching.. for interest point detection before applying the algorithm the SURF uses gaussian filter to smooth the image and get the effective and interesting points more accurately. The sum of the original image within a rectangle can be evaluated quickly using the integral image, requiring evaluations at the rectangle's four corners.

Surf Feature Extraction Method:

SURF uses a blob detector based on the Hessian matrix to find points of interest. The determinant of the Hessian matrix is used as a measure of local change around the point and points are chosen where this determinant is maximal. SURF also uses the determinant of the Hessian for selecting the scale. Given a point $p=(x, y)$ in an image I , the Hessian matrix $H(p, \sigma)$ at point p and scale σ , is shown.

Optical Character Recognition Algorithm (Ocr)

OCR is another feature extraction method to extract the text and numbers on the currency. Optical character recognition is used to detect the characters of different form present in the image. So we can extract few features depending on the values on the currency. MATLAB provides a predefined implementation of OCR. We can use it to extract the features that we want.

In order to recognize many variations of the same character, features that are invariant to certain transformations on the character need to be used. Invariants are features which have approximately the same values for samples of the same character that are, for example, translated, scaled, rotated, stretched, skewed, or mirrored

Mean and Standard Deviation

Mean and standard deviation of successive pixel values is also to be calculated and considered as the feature. Mean and standard deviation of pixel values obtains the feature depending on the color of the objects and their positions. As on any currency the arrangement of elements and color, font of the elements remains same.

Thus the features extracted using SURF, OCR and mean standard deviation we collect them and store it in a csv file format to apply classification algorithm and train the system.

Dataset Format

Dataset holds the features that are extracted using feature extraction methods. The dataset may be in the format of CSV file. Where it contains many columns for concentrated point's average, OCR recognized numeric value, mean of pixels, standard deviation of pixels, actual class label. This dataset is used to train the classifier.

Classification Methods

As the dataset we obtained is completely numeric the K-nearest neighbor algorithm can be used to train the classifier. KNN algorithm is best to use while training the classifier where there is a small dataset and it has numeric values. Basically KNN falls under supervised learning algorithms. KNN algorithm is a Lazy learner which starts comparing with the each and every tuple in the dataset and finds the class under which it falls. It is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The distance to the k nearest neighbor can also be seen as a local density estimate and thus is also a popular outlier score in anomaly detection. The larger the distance to the k-NN, the lower the local density, the more likely and the query point is an outlier.

Implementation Of Algorithms

Step 1: collect the currency pictures that are to be used to train the system.

Step 2: implement a feature extraction method and extract the features and save it into a dataset.

Step 3: train the classification system using KNN algorithm. (Note: give more coefficient value that have more impact on the output)

Step 4: Test the system by giving unknown image to system and find the accuracy of the system.

Features that differentiates from currently existing system:

As the three feature extraction algorithms are used the results are more appropriate. The system can identify the value of the currency even if the input is mirror image to the actual image. It detects the value in whatever direction the image may take, as OCR feature extraction algorithm is used. Once the features are extracted there is no need of holding the images in the dataset. The only values that we store in our dataset is numeric values. So it results in reduced size of database and easy to store and retrieve the data. As the coefficients are given according to the weightage of the feature the classification algorithm is more efficient.

A Real Life Example

Consider the currency counting machine which has to scan all the mixed currencies of different countries and find the total according to the selected country currency value and displays it. To do this the machine has to be intelligent enough to convert all the currencies accordingly to a single form and find the total. Here is the situation where the currency value detection comes into consideration with efficient and effective calculations. It can also be used in ATM machines. It is very much helpful for blind people, when the currency is scanned and given to the system it automatically

detects and if connected to text to voice conversion system it speaks out the result and the person can identify the currency value that he scanned.

Conclusion

Here by we conclude that the total amount of the currency can be calculated using currency converting formulas and the detected value by classifier by summing up the results after conversion. Using multiple feature extraction methods makes the system more efficient and accurate. Here, SURF is used to find the concentrated points and positions, OCR is used to find the characters and numbers on the currency, the color and texture is also considered as the feature by obtaining mean and standard deviation. While training the classifier it is important to prioritize the features that impact more on the output and add a high coefficient value such that the results become more sensitive to the prioritized feature.

2.4. Detection of Fake Currency using Image Processing

ABSTRACT:

In recent years a lot of fake currency note is being printed which have caused great loss and damage towards society. So, it has become a necessity to develop a tool to detect fake currency. This project proposes an approach that will detect fake currency note being circulated in our country by using their image. Our project will provide required mobility and compatibility to most peoples as well as credible accuracy for the fake currency detection. We are using image processing and cloud storage to make this app portable and efficient.

INTRODUCTION:

Fake currency detection is a serious issue worldwide, affecting the economy of almost every country including India. Currency duplication also known as counterfeit currency is a vulnerable threat on economy. It is now a common phenomenon due to advanced printing and scanning technology. The possible solutions are to use either chemical properties of the currency or to use its physical appearance. The approach presented in this paper is based upon physical appearance of the Indian currency. Image processing algorithms have been adopted to extract the features such as security thread, intaglio printing (RBI logo) and identification mark, which have been adopted as security features of Indian currency. Hence, we propose a more user friendly and portable solution to this problem in form of an mobile app coupled with cloud storage.

ALGORITHM USED

1. SVM Algorithm: In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analysis data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non- probabilistic binary linear classifier

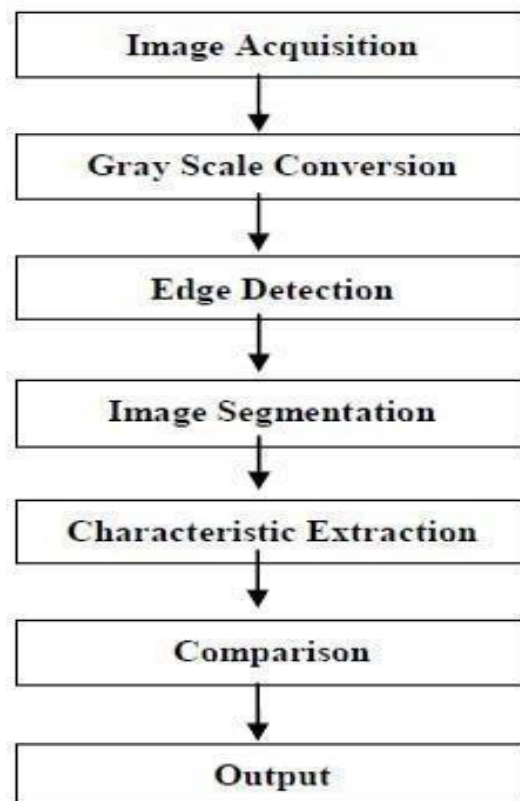
(although methods such as Platt scaling exist to use SVM in a probabilistic classification setting).

CONCLUSION AND FUTURE SCOPE

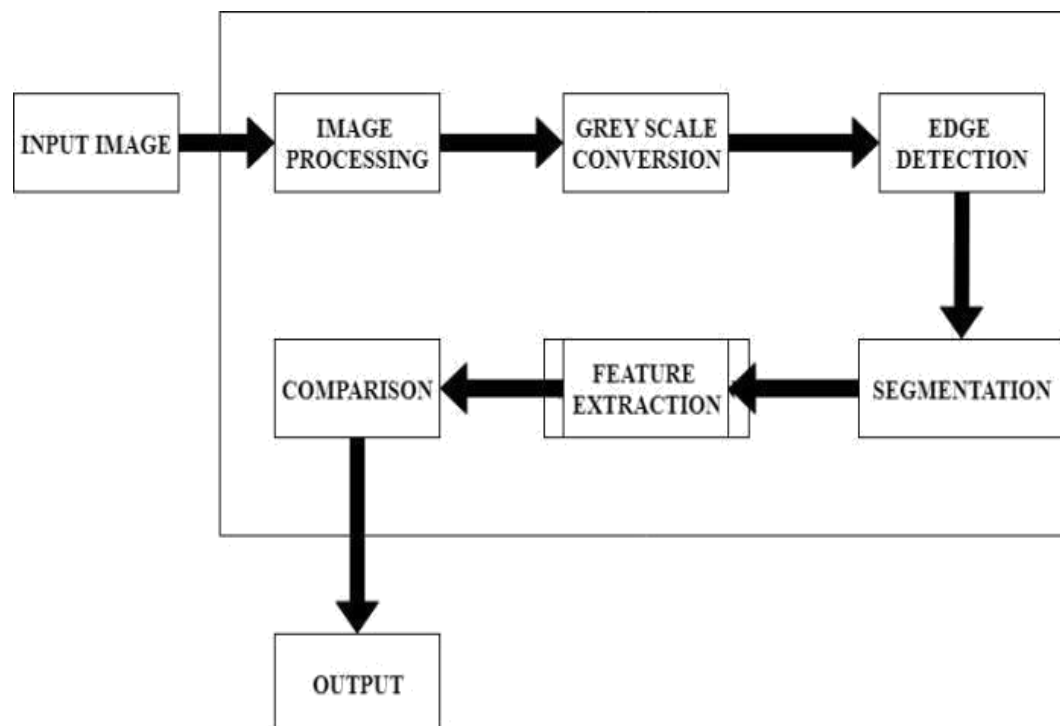
Our System will be helpful for the regular peoples who are technically not involved in daily life with background processes. A smartphone app will provide its user an concise way to perform a very necessary task. In forthcoming future, as discussed by “Akanksha Upadhyaya Research Scholar, Vinod Shokeen Associate Professor, Garima Srivastava.” In their study that precision of above 99% can be achieved with image processing and supervised learning. Our proposed system could replace the hardware system in some initial stages of currency verification process.

Chapter 3

System Architecture / Ideation Map:



Flowchart to Detect Fake Currency



Architecture diagram of proposed System

Chapter 4

Machine learning

What are the 7 steps of machine learning?

7 Steps of Machine Learning

- Step 1: Gathering Data. ...
- Step 2: Preparing that Data. ...
- Step 3: Choosing a Model. ...
- Step 4: Training. ...
- Step 5: Evaluation. ...
- Step 6: Hyper parameter Tuning. ...
- Step 7: Prediction.

Introduction:

In this blog, we will discuss the workflow of a Machine learning project this includes all the steps required to build the proper machine learning project from scratch.

We will also go over data pre-processing, data cleaning, feature exploration and feature engineering and show the impact that it has on Machine Learning Model Performance. We will also cover a couple of the pre-modelling steps that can help to improve the model performance.

Python Libraries that would be need to achieve the task:

1. Numpy
2. Pandas
3. Sci-kit Learn
4. Matplotlib

Understanding the machine learning workflow

We can define the machine learning workflow in 3 stages.

1. Gathering data
2. Data pre-processing
3. Researching the model that will be best for the type of data
4. Training and testing the model
5. Evaluation

Okay but first let's start from the basics

What is the machine learning Model?

The machine learning model is nothing but a piece of code; an engineer or data scientist makes it smart through training with data. So, if you give garbage to the model, you will get garbage in return, i.e. the trained model will provide false or wrong prediction

1. Gathering Data

The process of gathering data depends on the type of project we desire to make, if we want to make an ML project that uses real-time data, then we can build an IoT system that using different sensors data. The data set can be collected from various sources such as a file, database, sensor and many other such sources but the collected data cannot be used directly for performing the analysis process as there might be a lot of missing data, extremely large values, unorganized text data or noisy data. Therefore, to solve this problem Data Preparation is done.

We can also use some free data sets which are present on the internet. Kaggle and UCI Machine learning Repository are the repositories that are used the most for making Machine learning models. Kaggle is one of the most visited websites that is used for practicing machine learning algorithms, they also host competitions in which people can participate and get to test their knowledge of machine learning.

2. Data pre-processing

Data pre-processing is one of the most important steps in machine learning. It is the most important step that helps in building machine learning models more accurately. In machine learning, there is an 80/20 rule. Every data scientist should spend 80% time for data pre-processing and 20% time to actually perform the analysis.

What is data pre-processing?

Data pre-processing is a process of cleaning the raw data i.e. the data is collected in the real world and is converted to a clean data set. In other words, whenever the data is gathered from different sources it is collected in a raw format and this data isn't feasible for the analysis.

Therefore, certain steps are executed to convert the data into a small clean data set, this part of the process is called as data pre-processing.

Why do we need it?

As we know that data pre-processing is a process of cleaning the raw data into clean data, so that can be used to train the model. So, we definitely need data pre-processing to achieve good results from the applied model in machine learning and deep learning projects. Most of the real-world data is messy, some of these types of data are:

1. **Missing data:** Missing data can be found when it is not continuously created or due to technical issues in the application (IOT system).
2. **Noisy data:** This type of data is also called outliers, this can occur due to human errors (human manually gathering the data) or some technical problem of the device at the time of collection of data.
3. **Inconsistent data:** This type of data might be collected due to human errors (mistakes with the name or values) or duplication of data.

Three Types of Data

1. Numeric e.g. income, age
2. Categorical e.g. gender, nationality
3. Ordinal e.g. low/medium/high

How can data pre-processing be performed?

These are some of the basic pre — processing techniques that can be used to convert raw data.

1. **Conversion of data:** As we know that Machine Learning models can only handle numeric features, hence categorical and ordinal data must be somehow converted into numeric features.

2. **Ignoring the missing values:** Whenever we encounter missing data in the data set then we can remove the row or column of data depending on our need. This method is known to be efficient but it shouldn't be performed if there are a lot of missing values in the dataset.

3. **Filling the missing values:** Whenever we encounter missing data in the data set then we can fill the missing data manually, most commonly the mean, median or highest frequency value is used.

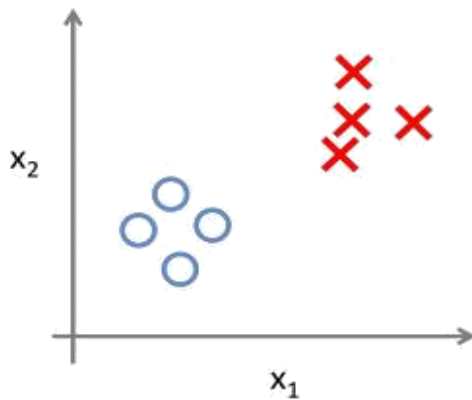
4. **Machine learning:** If we have some missing data then we can predict what data shall be present at the empty position by using the existing data.

5. **Outliers detection:** There are some error data that might be present in our data set that deviates drastically from other observations in a data set. [Example: human weight = 800 Kg; due to mistyping of extra 0]

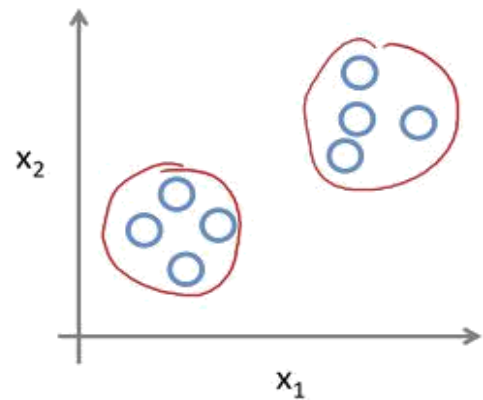
Researching the model that will be best for the type of data

Our main goal is to train the best performing model possible, using the pre-processed data.

Supervised Learning



Unsupervised Learning



Supervised Learning:

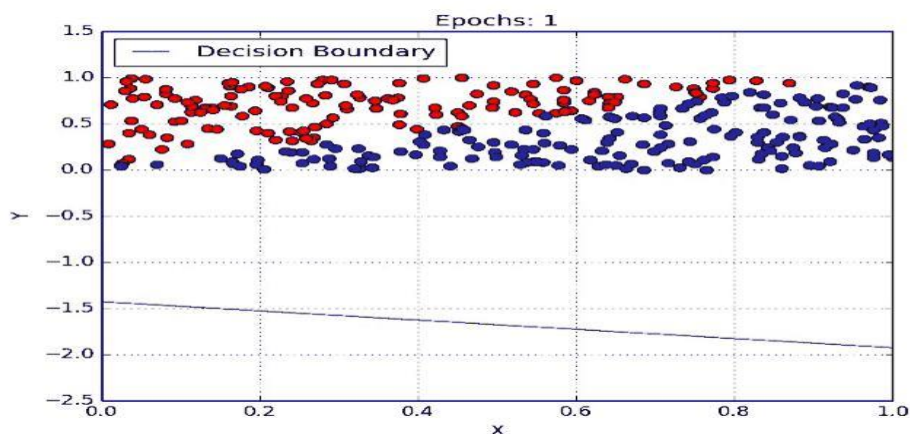
In Supervised learning, an AI system is presented with data which is labelled, which means that each data is tagged with the correct label.

The supervised learning is categorized into 2 other categories which are “**Classification**” and “**Regression**”.

Classification:

Classification problem is when the target variable is **categorical** (i.e. the output could be classified into classes — it belongs to either Class A or B or something else).

A classification problem is when the output variable is a category, such as “red” or “blue”, “disease” or “no disease” or “spam” or “not spam”.



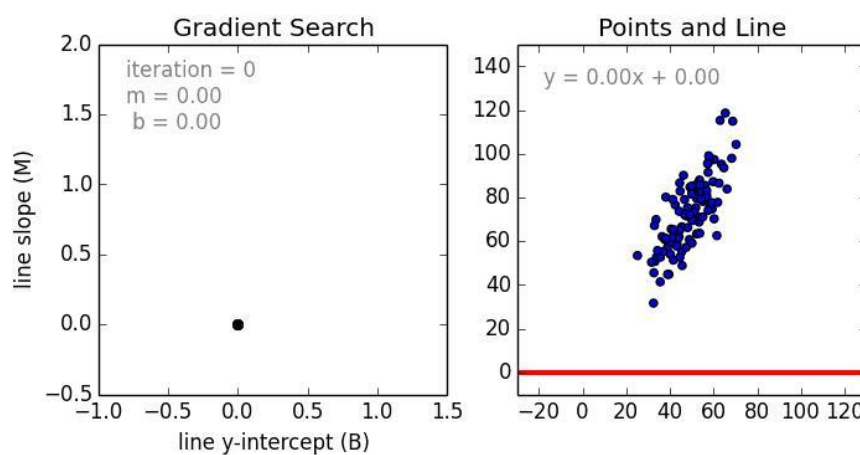
As shown in the above representation, we have 2 classes which are plotted on the graph i.e. red and blue which can be represented as 'setosa flower' and 'versicolor flower', we can image the X-axis as there 'Sepal Width' and the Y-axis as the 'Sepal Length', so we try to create the best fit line that separates both classes of flowers.

These some most used classification algorithms.

- **K-Nearest Neighbor**
- **Naive Bayes**
- **Decision Trees/Random Forest**
- **Support Vector Machine**
- **Logistic Regression**

Regression:

While a **Regression** problem is when the target variable is **continuous** (i.e. the output is numeric).



As shown in the above representation, we can imagine that the graph's X-axis is the 'Test scores' and the Y-axis represents 'IQ'. So we try to create the best fit line in the given graph so that we can use that line to predict any approximate IQ that isn't present in the given data.

These some most used regression algorithms.

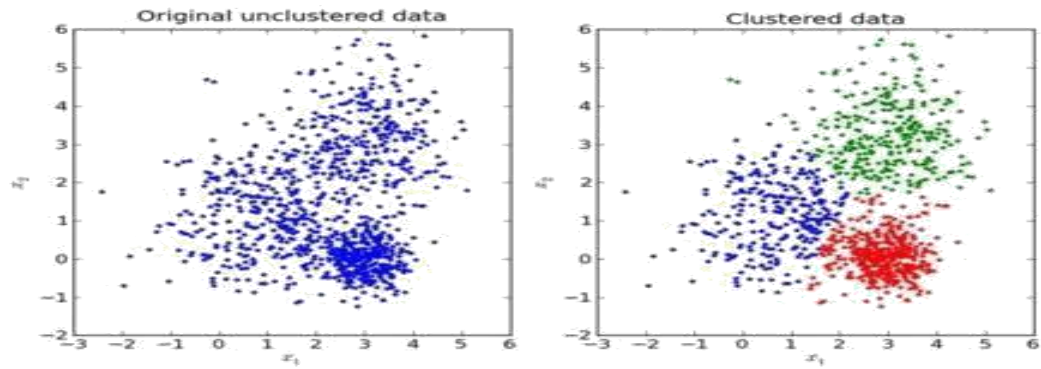
- **Linear Regression**
- **Support Vector Regression**
- **Decision Tress/Random Forest**
- **Gaussian Progresses Regression**
- **Ensemble Methods**

Unsupervised Learning:

The unsupervised learning is categorized into 2 other categories which are "**Clustering**" and "**Association**".

Clustering:

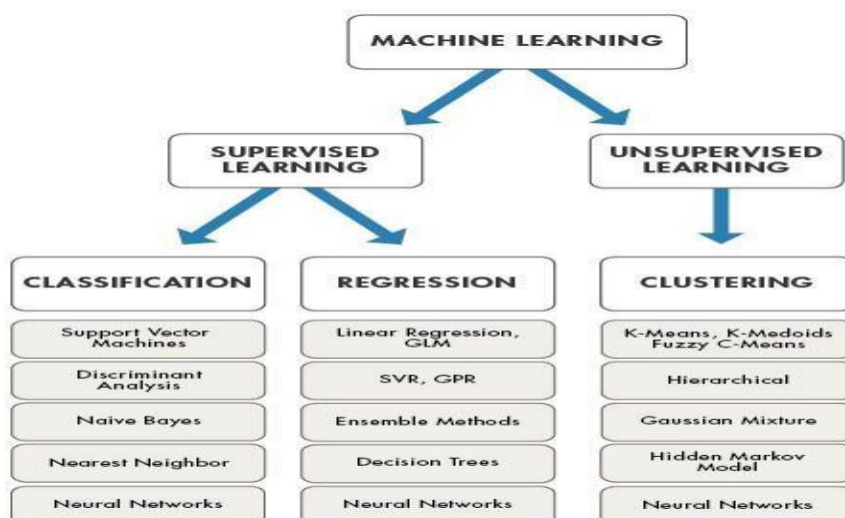
A set of inputs is to be divided into groups. Unlike in classification, the groups are not known beforehand, making this typically an unsupervised task.



Methods used for clustering are:

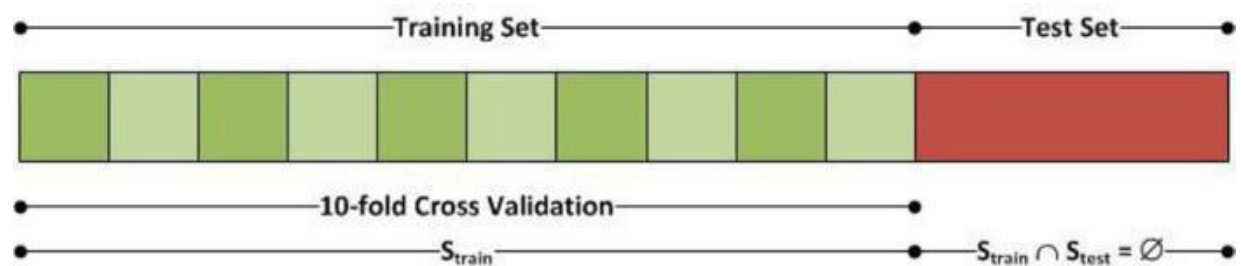
- Gaussian mixtures
- K-Means Clustering
- Boosting
- Hierarchical Clustering
- K-Means Clustering
- Spectral Clustering

Overview of models under categories:



4. Training and testing the model on data

For training a model we initially split the model into 3 three sections which are ‘**Training data**’ , ‘**Validation data**’ and ‘**Testing data**’. You train the classifier using ‘**training data set**’, tune the parameters using ‘**validation set**’ and then test the performance of your classifier on unseen ‘**test data set**’. An important point to note is that during training the classifier only the training and/or validation set is available. The test data set must not be used during training the classifier. The test set will only be available during testing the classifier.

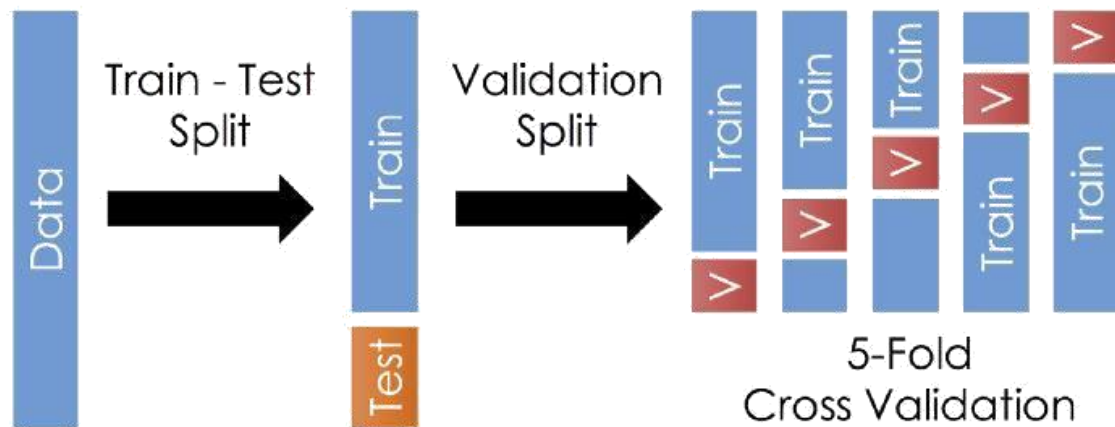


Training set:

The training set is the material through which the computer learns how to process information. Machine learning uses algorithms to perform the training part. A set of data used for learning, that is to fit the parameters of the classifier.

Validation set:

Cross-validation is primarily used in applied machine learning to estimate the skill of a machine learning model on unseen data. A set of unseen data is used from the training data to tune the parameters of a classifier.



Once the data is divided into the 3 given segments we can start the training process.

In a data set, a training set is implemented to build up a model, while a test (or validation) set is to validate the model built. Data points in the training set are excluded from the test (validation) set. Usually, a data set is divided into a training set, a validation set (some people use 'test set' instead) in each iteration, or divided into a training set, a validation set and a test set in each iteration.

The model uses any one of the models that we had chosen in step 3/ point 3. Once the model is trained we can use the same trained model to predict using the testing data i.e. the unseen data. Once this is done we can develop a confusion matrix, this tells us how well our model is trained. A confusion matrix has 4 parameters, which are '**True positives**', '**True Negatives**', '**False Positives**' and '**False Negative**'. We prefer that we get more values in the True negatives and true positives to get a more accurate model. The size of the Confusion matrix completely depends upon the number of classes.

n=165	Predicted: NO	Predicted: YES
Actual: NO	50	10
Actual: YES	5	100

True positives : These are cases in which we predicted TRUE and our predicted output is correct.

True negatives : We predicted FALSE and our predicted output is correct.

False positives : We predicted TRUE, but the actual predicted output is FALSE.

False negatives : We predicted FALSE, but the actual predicted output is TRUE.

We can also find out the accuracy of the model using the confusion matrix.

Accuracy = (True Positives + True Negatives) / (Total number of classes)

i.e. for the above example:

Accuracy = $(100 + 50) / 165 = 0.9090$ (90.9% accuracy)

5. Evaluation

Model Evaluation is an integral part of the model development process. It helps to find the best model that represents our data and how well the chosen model will work in the future.

To improve the model we might tune the hyper-parameters of the model and try to improve the accuracy and also looking at the confusion matrix to try to increase the number of true positives and true negatives.

Conclusion

In this blog, we have discussed the workflow a Machine learning project and gives us a basic idea of how a should the problem be tackled.

Chapter 5

SYSTEM DESIGN

Modules:

- Noise Filtering
- Image Acquisition
- Grey Scale Conversion
- Edge Detection
- Segmentation
- Feature Extraction
- Comparison

Noise filtering:

The Add Noise filter applies random pixels to an image, simulating the result of shooting pictures on high-speed film. This filter can also be used to reduce banding in feathered selections or graduated fills, to give a more realistic look to heavily retouched areas, or to create a textured layer.

Filtering is a technique for modifying or enhancing an image. For example, you can filter an image to emphasize certain features or remove other features. Image processing operations implemented with filtering include smoothing, sharpening, and edge enhancement.

Image Acquisition:

Step 1: Image Acquisition. The image is captured by a sensor

Step 2: Image Enhancement. ...

Step 3: Image Restoration. ...

Step 4: Color Image Processing. ...

Step 5: Wavelets. ...

Step 6: Compression. ...

Step 7: Morphological Processing. ...

Step 8: Image Segmentation.

Edge Detection:

Edge detection is an image processing technique for finding the boundaries of objects within images. It works by detecting discontinuities in brightness. Edge detection is used for image segmentation and data extraction in areas such as image processing, computer vision, and machine vision.

Steps:

- Noise reduction;
- Gradient calculation;
- Non-maximum suppression;
- Double threshold;

- Edge Tracking by Hysteresis.

Segmentation:

- To segment a market, you split it up into groups that have similar characteristics. You can base a segment on one or more qualities. Splitting up an audience in this way allows for more precisely targeted marketing and personalized content.
Types of Market Segmentation.
- A market segmentation strategy organizes your customer or business base along demographic, geographic, behavioral, or psychographic lines—or a combination of them. Market segmentation is an organizational strategy used to break down a target market audience into smaller, more manageable groups.

Feature Extraction:

- Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly to the raw data. ... An example of a simple feature is the mean of a window in a signal. Feature Extraction aims to reduce the number of features in a dataset by creating new features from the existing ones (and then discarding the original features). These new reduced set of features should then be able to summarize most of the information contained in the original set of features
- Feature extraction helps to reduce the amount of redundant data from the data set. In the end, the reduction of the data helps to build the model with less machine's efforts and also increase the speed of learning and generalization steps in the machine learning process

Chapter 6

Conclusions:

- Currency use is a necessity for survival and hence it is always necessary to keep in track of its originality.
- Paper currencies are used much more in India and hence a system to detect the fake currency is needed.
- As the new currencies are used in the market, the proposed system seems to be useful to detect the currency to be genuine or not.
- This system compares more features for feature extraction than other proposed systems.
- It also shows where the differences are in the currencies instead of simply displaying the result.
- This system can be further implemented for foreign currencies like Dollars, Euros, Taka, etc. as a future scope.

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Source Code:

code.py –

```
import cv2
import os
import numpy as np
import pickle

img = cv2.imread(r"Dataset\2000\2000front.jpeg") # reading the image
file
img1 = cv2.imread(r"Dataset\2000\2000back.jpeg")
res1 = cv2.resize(img, (800, 300)) # resizing the img for display
res2 = cv2.resize(img1, (800, 300)) # resizing the img for display
image = np.concatenate((res1, res2), axis=0) # concatenating images for
display

img_median = cv2.medianBlur(image, 3) # Add median filter to image
gray = cv2.cvtColor(img_median, cv2.COLOR_BGR2GRAY) # converting
to gray scale
edges = cv2.Canny(gray, 60, 180) # canny edge detection
th2 = cv2.adaptiveThreshold(edges, 255,
cv2.ADAPTIVE_THRESH_MEAN_C, cv2.THRESH_BINARY, 11, 10) #
segmentation using adaptive thresholding

cv2.imshow('original image', image) # original images
cv2.imshow('noise filtered', img_median) # filtered images
cv2.imshow('gray scale', gray) # gray scale
```

```
cv2.imshow('edge detected', edges) # edge detected
cv2.imshow('segmented', th2) # segmented
cv2.waitKey(0) # Wait for a key press to
cv2.destroyAllWindows() # close the img window
```

```
# for saving segmented image
#with open('saved.pkl', 'wb') as f:
#    pickle.dump(th2, f)
```

```
outfile = open('saved', 'wb')
pickle.dump(th2, outfile)
outfile.close()
```

test.py –

```
import cv2
import os
import numpy as np
from skimage import measure
from skimage.metrics import structural_similarity as
ssim #from skimage.measure import compare_ssim
import pickle
# for selecting the currency for checking
genuinity import tkinter as tk
from tkinter import filedialog

root = tk.Tk()
root.withdraw()
root.call('wm', 'attributes', '.', '-topmost', True)
file_path1 = filedialog.askopenfilename()
print(file_path1)
file_path2 = filedialog.askopenfilename()
print(file_path2)
img2 = cv2.imread(file_path1) # reading the image file
img3 = cv2.imread(file_path2)
res3 = cv2.resize(img2, (800, 300)) # resizing the img for display res4
= cv2.resize(img3, (800, 300)) # resizing the img for display image2 =
np.concatenate((res3, res4), axis=0) # for displaing images vertically
concatenating the images
```

```
img_median1 = cv2.medianBlur(image2, 3) # Add median filter to image
gray1 = cv2.cvtColor(img_median1, cv2.COLOR_BGR2GRAY) #
converting to gray scale
edges1 = cv2.Canny(gray1, 60, 180) # canny edge detection
th21 = cv2.adaptiveThreshold(edges1, 255,
cv2.ADAPTIVE_THRESH_MEAN_C, cv2.THRESH_BINARY, 11, 10) #
segmentation using adaptive thresholding
cv2.imshow('selected image', image2) # original images
cv2.imshow('noise filtered', img_median1) # filtered images
cv2.imshow('gray scale', gray1) # gray scale
cv2.imshow('edge detected', edges1) # edge detected
cv2.imshow('segmented', th21) # edge detected
cv2.waitKey(0) # Wait for a key press to
cv2.destroyAllWindows() # close the img window
```

```
# comparing saved image and test image of currency
# loading saved segmented image
```

```
infile = open('saved', 'rb')
th2 = pickle.load(infile)
infile.close()
```

```
(score, diff) = ssim(th2, th21, full=True) diff = (diff
* 255).astype("uint8") print("SSIM:
{}".format(score)) cv2.imshow('difference', diff)
cv2.waitKey(0) # Wait for a key press to
cv2.destroyAllWindows() # close the img window
```

```
from tkinter import messagebox
```

```
if score == 1:
    messagebox.showinfo("Message", "currency is genuine")
else:
    messagebox.showinfo("Message", "currency is fake")
```

Research Paper:

Evaluation of Machine Learning Algorithms for the Detection of Fake Bank Currency

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Abstract: The currency has a great meaning in everyday life. Thus currency recognition has gained a great interest for many researchers. The researchers have suggested diverse approaches to improve currency recognition. Based on strong literature survey, image processing can be considered as the most widespread and effective technique of currency recognition. This paper introduces some close related works of paper-currency recognition. This paper has explained a variety of different currency recognition systems. The applications have used the power of computing to differentiate between different types of currencies with the appropriate layer. Choosing the proper feature would improve overall system performance. The main goal of this work is to compare previous papers and literatures through reviews these literatures and identify the advantages and disadvantage for each method in these literatures. The results were summarized in a comparison table that presented different ways of reviewing the technology used in image processing to distinguish currency papers.

Keywords: fake currency, image processing, noise filtering, machine learning.

1. Introduction

Despite a decrease in the use of currency due to the recent growth in the use of electronic transactions, cash transactions remain very important in the global market. Banknotes are used to carry out financial activities. To continue with smooth cash transactions, entry of forged banknotes in circulation should be preserved. There has been a drastic increase in the rate of fake notes in the market. Fake money is an imitation of the genuine notes and is created illegally for various motives. These fake notes are created in all denominations which brings the financial market of the country to a low level. The various advancements in the field of scanners and copy machines have led the miscreants to create copies of banknotes. It is difficult for human-eye to recognize a fake note because they are created with great accuracy to look alike a genuine note. Security aspects of banknotes have to be considered and security features are to be introduced to mitigate fake currency. Hence, there is a dire need in banks and ATM machines to implement a system that classifies a note as genuine or fake. In the recent years, Soft computing techniques have been widely used to solve problems that are difficult to solve using conventional mathematical methods. Supervised learning techniques are widely used in classification problems. This paper evaluates supervised machine learning algorithms to classify genuine and fake notes, and compares algorithms on the basis of accuracy, sensitivity, and specificity. Consider someone wants to deposit money in the bank. The notes that are to be deposited are given to a human being to check for their authenticity. As the fake notes are prepared with precision, it is difficult to differentiate them from genuine ones. A recognition system must be installed to detect legitimacy of the note. The system should extract the features of the note using image processing techniques. These features will be given as input to the machine learning algorithm which will predict if the note is true or fake. Supervised machine learning techniques such as BPN and SVM were implemented. The dataset used to train these algorithms was collected by extracting features from banknote images. The dataset also classifies all the samples into a particular class i.e. genuine or forged. A comparative study of these techniques with respect to their accuracy, sensitivity, specificity and precision rate is shown. Currently, the use of paper money remains one of the main options for the exchange of products and services. However, one of the remaining problems is the detection of counterfeit banknotes, which increasingly resemble originals, making it difficult for someone who is not an expert in the field to detect them. On the other hand, there are machines for detecting counterfeit banknote; however, these are often expensive, so the identification and retention of counterfeits ends up falling on financial and government entities, with minimal community involvement. In order to solve this problem and to present alternative solutions, in the state-of-the art, there are proposals based on classical computer vision techniques. For example, from histogram equalization, nearest neighbour interpolation, genetic algorithms and fuzzy systems. However, the main problem of this type of methods is its low capacity of generalization for new examples as well as its accuracy. Another group corresponds to those methods based on deep learning w ac(DL) using convolutional neural networks (CNNs), which have outperformed to the classic machine learning techniques and humans too in classification tasks. Considering the

current importance of the CNNs in the field of computer vision, there are some proposals in the area of banknote recognition and counterfeit detection. For example, transfer learning (TL) with Histograms of Oriented Gradients for Euro banknotes, a YOLO net for Mexican banknotes or custom CNN architectures for dollar, Jordanian dinar and Won Korean banknotes have been proposed. However, one of the main disadvantages of proposals using CNNs that focus on fake banknote recognition is that there is no clarity about which design strategy is more appropriate, either custom or by transfer learning. When using transfer learning-based networks, there are many types of patterns that the network has learned, but they are not specific to the current task. On the other hand, custom networks are trained with a much smaller dataset than the pre-trained networks, but they specifically learn the patterns of this type of classification task. Another shortcoming found in the literature is that the impact of the freezing point (FP) of the pre-trained network on the performance of the classifier has not been analysed. According to the above, the main contributions of this research are as follows:

- A methodology to identify the best freezing point in models by transfer learning, for three different types of architectures: sequential, residual and Inception is proposed.

- A custom model inspired in AlexNet that has faster inference times in an embedded system than models by transfer learning is proposed.

- A comparative study for the fake banknote recognition task between a custom model and several models obtained by transfer learning, in terms of accuracy and inference times is given. The rest of the paper is organized as follows. Section presents the background of Convolutional Neural Networks and transfer learning. Section shows the proposed system of image acquisition and the used dataset. Section explains the proposed methodology for selecting the freezing point in the design by transfer learning. Section presents the proposed custom model. Section shows the results of the research. Finally, Section summarizes the work.

- Fake Currency has always been an issue which has created a lot of problems in the market.
- The increasing technological advancements have made the possibility for creating more counterfeit currency which are circulated in the market which reduces the overall economy of the country.

- There are machines present at banks and other commercial areas to check the authenticity of the currencies.
- But a common man does not have access to such systems and hence a need for a software to detect fake currency arises, which can be used by common people.

- This proposed system uses Image Processing to detect whether the currency is genuine or counterfeit.

2. Literature Survey

2.1. Detection of Fake currency using Image Processing

This project proposed fake currency detection using image processing. In image pre-processing the image was cropped, adjusted and smoothed. Then the image converted into grey scale. After conversion the edges are detected. In edge detection used the sobel operator. Next the image segmentation is applied. After segmentation the features are extracted. Finally compared and find the currency original or fake.

2.2 Analysis of Banknote Authentication System using Machine Learning Techniques

After analysing various techniques used to detect forged banknotes, this paper presents banknote authentication for recognizing the banknote as genuine or fake by using two supervised learning techniques. Extensive experiments have been performed on banknotes dataset using both the models to find the best model suitable for classification of the notes. ROC and other metrics have been calculated to compare the performances of both the techniques. The result shows that backpropagation neural network outperforms support vector machine and gives 100% success rate. These techniques are an efficient way of solving the problem for all banking machines that accept all types of notes. In future, this work can be extended by categorizing the notes into different categories as Genuine, Low-Quality forgery, High-quality forgery, Inappropriate ROI.

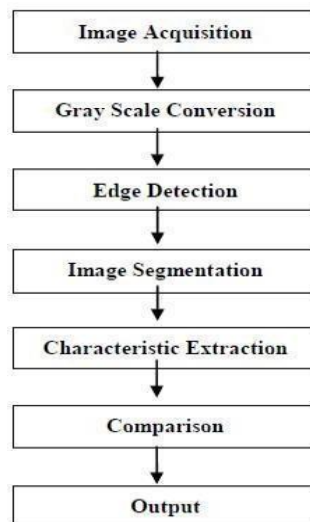
2.3. Currency Value Detection and Counting using Feature Extraction and Classification Algorithms

They conclude that the total amount of the currency can be calculated using currency converting formulas and the detected value by classifier by summing up the results after conversion. Using multiple feature extraction methods makes the system more efficient and accurate. Here, SURF is used to find the concentrated points and positions, OCR is used to find the characters and numbers on the currency, the colour and texture is also considered as the feature by obtaining mean and standard deviation. While training the classifier it is important to prioritize the features that impact more on the output and add a high coefficient value such that the results become more sensitive to the prioritized feature.

2.4. Detection of Fake Currency using Image Processing

Their System will be helpful for the regular peoples who are technically not involved in daily life with background processes. A smartphone app will provide its user an concise way to perform a very necessary task. In forthcoming future, as discussed by “Akanksha Upadhyaya Research Scholar, Vinod Shokeen Associate Professor, Garima Srivastava.” In their study that precision of above 99% can be achieved with image processing and supervised learning. Our proposed system could replace the hardware system in some initial stages of currency verification process.

3. System Architecture



4. Proposed System

4.1 Noise filtering:

The Add Noise filter applies random pixels to an image, simulating the result of shooting pictures on high-speed film. This filter can also be used to reduce banding in feathered selections or graduated fills, to give a more realistic look to heavily retouched areas, or to create a textured layer. Filtering is a technique for modifying or enhancing an image. For example, you can filter an image to emphasize certain features or remove other features. Image processing operations implemented with filtering include smoothing, sharpening, and edge enhancement.

4.2 Image Acquisition:

- Step 1: Image Acquisition. The image is captured by a sensor
- Step 2: Image Enhancement.
- Step 3: Image Restoration.
- Step 4: Colour Image Processing
- Step 5: Wavelets
- Step 6: Compression
- Step 7: Morphological Processing.
- Step 8: Image Segmentation.

4.3 Edge Detection:

Edge detection is an image processing technique for finding the boundaries of objects within images. It works by detecting discontinuities in brightness. Edge detection is used for image segmentation and data extraction in areas such as image processing, computer vision, and machine vision.

Steps:

1. Noise reduction;
2. Gradient calculation;

3. Non-maximum suppression;
4. Double threshold;
5. Edge Tracking by Hysteresis.

4.4 Segmentation:

To segment a market, you split it up into groups that have similar characteristics. You can base a segment on one or more qualities. Splitting up an audience in this way allows for more precisely targeted marketing and personalized content. Types of Market Segmentation. A market segmentation strategy organizes your customer or business base along demographic, geographic, behavioural, or psychographic lines—or a combination of them. Market segmentation is an organizational strategy used to break down a target market audience into smaller, more manageable groups.

4.5 Feature Extraction:

Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly to the raw data. ... An example of a simple feature is the mean of a window in a signal. Feature Extraction aims to reduce the number of features in a dataset by creating new features from the existing ones (and then discarding the original features). These new reduced set of features should then be able to summarize most of the information contained in the original set of features. Feature extraction helps to reduce the amount of redundant data from the data set. In the end, the reduction of the data helps to build the model with less machine's efforts and also increase the speed of learning and generalization steps in the machine learning process.

5 Conclusions:

Currency use is a necessity for survival and hence it is always necessary to keep in track of its originality. Paper currencies are used much more in India and hence a system to detect the fake currency is needed. As the new currencies are used in the market, the proposed system seems to be useful to detect the currency to be genuine or not. This system compares more features for feature extraction than other proposed systems. These methods can be used in machines like ATM's where people deposit and withdraw cash on regular basis. It also shows where the differences are in the currencies instead of simply displaying the result. This system can be further implemented for foreign currencies like Dollars, Euros, Taka, etc. as a future scope.

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Cash is a ton of significance in daily existence. In this manner, the issue of monetary exposure has charmed numerous scientists. Scientists offer an assortment of ways of fund-raising. In view of broad writing research, picture advancement can be viewed as an ordinary and productive method for deciding cash. This page presents a portion of the lucrative exercises. This article depicts the various ways of bringing in cash. The program utilized the computational influence to separate the sorts of cash and the proper part and to pick the right exhibition that will work on the general execution of the framework. The primary reason for this paper is to audit the writing and writing that went before the survey of these books and to distinguish the advantages and disadvantages of each type of writing. The outcomes gathered in the similar table show the various strategies for controlling the innovation utilized in picture handling to separate solicitations.

Keywords: fake cash, picture handling, commotion sifting, AI,

1. Introduction

In spite of the new log jam in the utilization of electronic items, the utilization of cash is still vital in the worldwide market. Cash is utilized for monetary purposes. Fake notes available for use should be maintained in control to keep exchanging cash. How much fake cash in the market has expanded essentially? Fake cash is a fake money and is made illicitly for an assortment of reasons. Fake notes are made in all monetary forms, decreasing the public monetary market. Different advances in scanner and duplicate prompted note creators. Counterfeit records are rare on the grounds that they are intended to resemble genuine data. To diminish fraud, monetary security should be considered. Consequently, there is a critical requirement for banks and ATMs to lay out a framework for making genuine or counterfeit notes. As of late, computational innovation has been broadly used to take care of mind boggling issues utilizing standard insights. The learning technique is broadly utilized in sequencing strategy. This page looks at AI devices to execute continuous records, and analyzes calculations in light of genuine, passionate, and interesting. Assume somebody needs to store in a kept the individual whether they are valid. Counterfeit archives are hard to recognize from genuine papers since they are very much planned. A notice framework should be set up to confirm that the archive is legitimate. The framework should extricate data utilizing picture handling innovation. These properties will be remembered for the calculation to decide whether the archive is valid or misleading. Executing AI techniques like BPN and SVM. The classes of data utilized in the preparation of these calculations were broke down and gathered in notes. Entries are classified into explicit classifications, valid or bogus. The review thinks about trustworthiness, feeling, specifically, and the speed at which this approach is illustrated. Currently, the use of paper money remains one of the main options

for the exchange of products and services. However, one of the remaining problems is the detection of counterfeit banknotes, which increasingly resemble originals, making it difficult for someone who is not an expert in the field to detect them. On the other hand, there are machines for detecting counterfeit banknotes; however, these are often expensive, so the identification and retention of counterfeits ends up falling on financial and government entities, with minimal community involvement. In order to solve this problem and to present alternative solutions, in the state-of-the-art, there are proposals based on classical computer vision techniques. For example, from histogram equalization, nearest neighbour interpolation, genetic algorithms and fuzzy systems. However, the main problem of this type of methods is its low capacity of generalization for new examples as well as its accuracy. Another group corresponds to those methods based on deep learning (DL) using convolutional neural networks (CNNs), which have outperformed the classic machine learning techniques and humans too in classification tasks. Considering the current importance of the CNNs in the field of computer vision, there are some proposals in the area of banknote recognition and counterfeit detection. For example, transfer learning (TL) with Histograms of Oriented Gradients for Euro banknotes, a YOLO net for Mexican banknotes or custom CNN architectures for dollar, Jordanian dinar and Won Korean banknotes have been proposed. However, one of the main disadvantages of proposals using CNNs that focus on fake banknote recognition is that there is no clarity about which design strategy is more appropriate, either custom or by transfer learning. When using transfer learning-based networks, there are many types of patterns that the network has learned, but they are not specific to the current task. On the other hand, custom networks are trained with a much smaller dataset than the pre-trained networks, but they specifically learn the patterns of this type of classification task. Another shortcoming found in the literature is that the impact of the freezing point (FP) of the pre-trained network on the performance of the classifier has not been analysed.

- A custom model inspired in AlexNet that has faster inference times in an embedded system than models by transfer learning is proposed.
- A comparative study for the fake banknote recognition task between a custom model and several models obtained by transfer learning, in terms of accuracy and inference times is given. Section explains the proposed methodology for selecting the freezing point in the design by transfer learning. Section presents the proposed custom model. Section shows the results of the research. Finally, Section summarizes the work.
- Fake cash has created a ton of issues on the lookout. • With the appearance of innovation, fake cash has been coursing on the lookout, decreasing the country's general economy.
- Banks and other specialty units have cash machines. • However, since customary individuals can't get such a framework, fake cash acknowledgment programming is required and standard individuals.
- The picture handling decide if the money is fake or fake.

2. Literature Survey

2.1. Detection of Fake currency using Image Processing

The undertaking means to identify fake banknotes by creating pictures. The picture was made, altered, and rearranged before it was handled into a picture. The picture will then, at that point, be scaled. After the change, recognize the gatherings. You utilized a running sobel as opposed

to understanding. Coming up next is an incomplete picture. Discard things independently. Then, at that point, look at genuine or fake monetary standards.

2.2

Subsequent to dissecting the different strategies used to observe fake banknotes, this report presents takes note of that validate or bogus utilizing two exploration techniques. To give a genuine illustration of how to order notes, broad exploration was led on informational index notes utilizing two models. ROC and different boundaries were determined to look at the presentation of the two advancements. The response is that brain network rearrangement is superior to vector machines and gives 100 percent achievement. This strategy is the most effective way to tackle the issue of all bank machines that acknowledge a wide range of banknotes. Later on, the action can be extended to various classifications, like valid, misleading, positive, bogus, and bogus ROI.

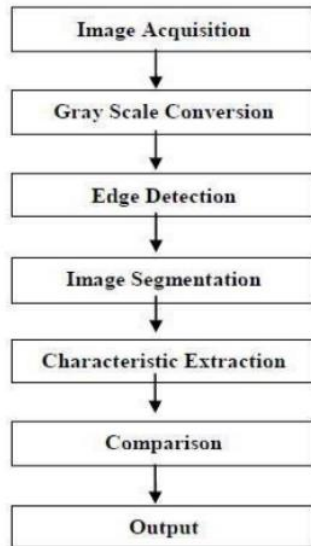
2.3.

They reason that the aggregate sum can be determined utilizing the worth communicated by the classifier as money transformation and the profit from the outcome after the change. The utilization of numerous extraction techniques makes the framework more proficient and successful. Here SURF is utilized to look for focuses and areas, OCR is utilized to track down cash, letters and numbers, and tones and surfaces are utilized to track down ways of recognizing. While sorting preparing, it is critical to focus on and increase the value of the most useful parts of efficiency so the outcomes are better in the needs.

2.4. Detection of Fake Currency using Image Processing

Their framework will help normal individuals who are not associated with day to day existence and exercises. The portable application will give clients the least demanding method for accomplishing truly necessary work. Further conversation by "Akanksha Upadhaya Scholar, Vinod Shoken Associate Professor, Garima Srivastava". As per their examination, beyond what close to 100% of data can be gotten to through picture handling and controlled learning. Our extraordinary framework can supplant the framework equipment in the initial segment of the cash control.

3. System Architechure



4. Proposed System

4.1 Noise filtering:

Add an uproarious channel utilizing exceptional pixels to rapidly contrast video results with films. The channel can be utilized to diminish the arrangement of chosen wings or to finish reviewing, to cause them to seem reasonable in the most monotonous segments, or to make a degree of composing. Channels are a method for changing over and upgrade pictures. For instance, you can channel a picture to feature a few highlights or erase different elements. The imaging system was performed with the assistance of channels, for example, smoothing, honing and sideways lifting.

4.2 Image Acquisition:

Stage 1: Take an image. Picture caught by contact

Stage 2: Image handling

Stage 3: Recover the picture

Stage 4: Image handling

Stage 5: Wave

Stage 6: Delete

Stage 7: Adjust the morphology accurately.

Stage 8: Figure segment.

4.3 Edge Detection:

Edge show is a picture handling procedure that tracks down the limits of items in a picture² It works by knowing how to remain in the light. Recognize parts of picture extraction mining.

Steps:

1. Sound decrease;
2. Count gradually;
3. Boundless treachery;
4. Two times;
5. Beach front control and hysteresis.

4.4 Segmentation:

Separating the market, partitioning it into bunches with comparable things. You can make areas in light of at least one quality. Diminishing the crowd in this manner prompts really publicizing and content. Kind of part of the market. Market isolation techniques address your clients or organizations in light of a vote-based system, geology, morals, and brain science, or both. A piece of the market is a hierarchical technique used to lessen portion of the overall industry in little, very much overseen gatherings.

4.5 Feature Extraction:

A unique download is a method for changing over a snippet of data in a manner that can be handled while holding the first data. This gives preferred outcomes over involving a direct machine for essential information. ... An illustration of a straightforward component is the normal of the image. The motivation behind the component is to make new elements (and afterward leave the first properties) from the typical undertakings that ascertain the quantity of introduced properties. These new deductible resources should have the option to sum up the majority of the data contained in the first action. Downloading highlights diminishes how much information that is more than the informational collection. All things considered, information decrease assists with making machines with less power, and expands the speed of speeding up learning and general perception in AI.

5 Conclusions:

The utilization of cash is fundamental for our endurance, so the first attributes should constantly be checked. Paper is broadly utilized in India, so a phony impersonation framework is required. As new cash is spent on business sectors, the framework offered is by all accounts significant in getting the reality of cash. The framework analyzes a great deal of things to dumping more than the reverse way around. Rather than simply showing the responses, it shows where the distinction in cash is. The framework can be executed in unfamiliar monetary forms like dollars, euros and taka.

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