Philippine Paper Bills Authenticator for the Blind using Image Processing

by

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Chapter 1

INTRODUCTION

The value of money is easily grasped by the fact that nearly all of our tasks are performed and completed using the currency. With massive changes in the economy as well as in human needs, the value of money is growing every day. The world revolves around money. When it comes to their everyday needs, some individuals intentionally create and use counterfeit money, and as a result, this type of money is being used across the economy [1]. A report from Manila Bulletin in 2021 says that the central bank seized P480,000 worth of counterfeit money in the first nine months of that year. The report also said that approximately 12,000 pieces of counterfeit money had been confiscated from criminals in the previous ten years [1]. Another case of counterfeit money was in May 2019. Three men were arrested after peddling fake cash in casinos. The National Capital Region Police Office (NCRPO) warned the public to be aware of counterfeit money [2]. Committing and proven in this type of crime will result in up to 12 years in prison and a fine of up to 2 million pesos. Throughout their lives, blind people struggle to do their daily activities effectively. Being independent will be hard for them. Giving and receiving money by buying their needs and riding public transportation can be an issue because they will have difficulty identifying money and are also prone to scams. Determining the amount and authenticity of the money is one of the struggles that blind people face.

Analyzing and identifying Philippine Paper Bills can be classified into image processing methods and UV light. Image processing is the widely used method to remember things that a visually impaired person cannot see. UV light is a piece of instrument that can locate non-visible marks on a paper bill. Hanish Aggarwal et al. [3] developed a method in which the acquired picture is localized using a localization approach, and the rupee denomination is recognized (Indian currency). Image edge detection is one of the most critical pieces of information in an image since it may represent the shape of a target, its relative position inside the target region, and other crucial details. A MATLAB GUI program was developed that acquired and processed the image through Canny Edge Technology. The Canny Edge algorithm proved a robust method of detecting fake bills through OVD security features, revealing a statistically significant detection proportion under a 5% significance level for the four cases under test [4]. The counterfeit prevention element of paper currency is the mechanism that performs the processing necessary to prevent paper currency counterfeiting [5], recovering the ultraviolet (UV) pattern from the currency that reflected fluorescent ink when illuminated by UV. Currently, several nations utilize UV patterns to avoid counterfeiting. Proposed is the GMM-based separation of the UV image into the UV pattern and background. The proposed approach is validated by comparing the results to Otsu's method [5].

Conventionally, currency-identifying systems are based on a smartphone application, such as using the camera to provide bill information. However, using a smartphone application has many disadvantages in reading and identifying the currency, such as limited features, inaccurate information, inability to recognize the state of the money, and cannot prove if the currency is fake. Another problem with the current authenticator is that some of the devices only detect level 1 features of the security. Another existing problem is the design and maintenance of the device, as the current procedure of money counterfeit detection devices requires introducing money into the system to be scanned, and the machine must be constantly cleaned. The disadvantages can be solved using an algorithm, UV light, and image processing.

The objective of the study is to develop a device that authenticates Philippine paper bills for the Blind using Image Processing. Specifically, the study aims: (1) to design a Philippine paper bill authenticator for the blind that detects level 1 and level 2 security features; (2) to utilize different algorithms such as Convolutional Neural Network, Canny Edge detection, Hough Line Transform, Optical Character Recognition, and Gaussian mixture model that will detect the level 1and level 2 security features of Philippine currency; (3) to add an audio prompt element that can assist visually challenged individuals into the counterfeit detection; (4) utilizing confusion matrix to validate the accuracy and functionality of the device for each currency.

The proposed device will detect whether the paper bills are authentic or fake with the use of image processing, Ultraviolet light, and algorithms. With this, it can help blind people determine the amount of the bill they are holding and prevent them from being cheated on or scammed.

Determining the authenticity of the Philippine paper bills released by the Banko Sentral ng Pilipinas will be the scope and limitation of the project. The device will not recognize the old generation of Philippine paper bills, the new one thousand-peso bill, and other countries' paper bills. The device will not say if the bill is dilapidated. Additionally, coins will also not be recognized by the device.

Chapter 2

REVIEW OF RELATED LITERATURE

This chapter combines concepts, ideas, approaches, algorithms, and completed and published investigations that give and substantiate the pertinent material for this study.

2.1 Counterfeit Detection Machine

Many studies are being done on finding counterfeit money or currency, and one of them is currency verification using an image processing system that explains how to verify the Indian rupee using image processing methods [6]. The technique includes several steps: image processing, edge detection, picture segmentation, characteristic extraction, and image comparison. Several research solutions have been offered in the past to verify the validity of the banknotes. A system for verifying currency was proposed employing image processing based on the extraction of features. For Indian banknotes, the solution was used. Edge detection and picture segmentation were employed between legitimate and fake currency [6].

A UML activity model for the Rs 2000 currency note for the Indian rupee was provided to describe the dynamic aspects of counterfeit cash identification. For security threads in the form of strips, they have employed class descriptions for genuine and counterfeit images of the currency and applied a comparison of block pixels to distinguish real and fake currency [7]. An image processing-based method for identifying counterfeit Indian currency has also been presented to detect forgeries, and the authors have used the embedded latent image and security thread. After extracting and encoding the security features, a clustering approach called k-means is used for classification. To determine if the note is fake or real, the latent picture is segmented using template matching, encoded using HOG descriptors, and then classed using an SVM model [8].

Another way of detecting currency using image processing involves comparing a returned note to an image from an existing notes database as a template [9]. The method utilized recognition of bank notes (notes) and compared it with other recognition techniques like Local Binary Pattern (LBP), Image Subtraction, and Gabor Wavelet.

Each country's characteristic has become a variable for the automatic recognition of currency notes [10]. The approach was made to reduce notes that were erroneously rejected. Edge representation will be fair among new or old damaged notes with the deployment of edge detection immediately following the transformation, improving robustness in the case of noise. Additionally, the number of edges discovered in the row order of the notes in a particular categorization is used along with a three-layer back propagation neural network.

2.2 Level 1 and Level 2 Security Features for Counterfeit

At a point of sale, cash transactions typically happen promptly and automatically [11]. When looking closely at the banknote, people may not allow themselves enough time, or they may feel embarrassed. Paying close attention to the security features is a reliable method for effectively authenticating a banknote. There are two ways that attentional orienting can happen: top-down and bottom-up. Due to the nature of the scene and stimulus saliency, bottom-up attention is typically used reflexively [12]. However, the capture of attention can be avoided by an inhibitory mechanism that suppresses the major stimulus [13].

Furthermore, figure 1 shows the three security levels in counterfeit cards. Thus, it is possible to view Level 1 features with the naked eye. They are, therefore, simple for field inspectors to authenticate. Since Level 2 features are covert, only skilled examiners utilizing magnification or another method instrument may see them. They are invisible to the naked eye.

The last description of Level 3 features is that they are forensic in nature and require skilled examiners and complex laboratory apparatus for authentication [14].

Figure 2. 1 Three document security feature levels

The BSP conducts research and comparative study on security features offered by international vendors and employed by other central banks. Four stages of authentication—from detailed visual inspection to more involved laboratory and forensic analysis of suspected counterfeits—can be accomplished using the security measures available [15]. These include:

1) *Level I.*

Security features that the public can easily recognize without using a particular instrument. These are the "look, feel, tilt" elements in the notes, such as watermark, security thread, security fibers, and others.

2) *Level II*

Security features are recognizable by professional cash handlers/bank tellers using magnifying lenses or ultraviolet light. Examples are fluoro-phosphorescent features, security fibers, and microprinting.

3) Level III

The hidden or covert security features are reserved for the Bangko Sentral use.

4) Level IV

Forensic security features for the use of law enforcers in testifying whether a banknote is genuine or counterfeit. These are detectable at specialized laboratories.

2.3 Image acquisition

Image acquisition is collecting a picture from a source, typically hardware systems such as cameras, sensors, etc. It is the first and most crucial stage in the workflow sequence because the system cannot perform actual processing without an image. Image is acquired by the digital camera by applying the white backlighting against the paper currency so that the hidden attributes can appear on the money image [16].

Figure 2. 2 User Interface of An Image Acquisition

Image acquisition is the first step in achieving the objective. Once the image has been acquired, it is processed through several stages. The image can be captured with either a camera or a scanner. The image must contain all visible features[17]. An image can be described as the two-dimensional function f(x,y), where (x, y) is a two-dimensional coordinate and f is the intensity of that coordinate. Each coordinate position is denoted by the term pixel. Pixel is the smallest image unit, also known as a picture element or pel. Therefore, digital images are comprised of pixels, where each pixel represents the color (or gray level for black-and-white images) at a particular position. A pixel is like a tiny dot of a specific color [18].

1) Black and White Images

Images in black and white consist of various hues of gray. These values range from 0 to 255, where 0 represents black, 255 represents white, and intermediate numbers represent multiple shades of black and white. Grayscale refers to the range of neutral tonal values (shades) from black to white[19].

2) Color Image

Color images are composed of pixels of various hues. Color may represent a significantly more comprehensive range of values than grayscale. Seven to ten million shades can be perceived by the human eye. Electronic color capture and the display is difficult. RGB (Red, Green, Blue) is the most widely used color model[19].

Bits/Digital Image type	Shades/colors
8 bits black and white image	256 shades
24 bits colored	16.8 million color
10 bits black and white image	1024 shades
30 bits colored	1 billion color
12 bits black and white image	4096 shades
36 bits colored image	68.7 billion colors

Table 2. 1 Shades/Colors Depends on the Bits Required to Represent the Digital Image

Essentially, the sensor converts illumination energy into a digital image. The concept is that incoming light energy is converted into voltage by combining input electrical energy and responsive sensor material. The output waveform is the sensor's response, which is then transformed into a digital image. The 2-dimensional function f. (x, y) represents the image. A picture must have a non-zero and finite number[18].

$$0 < f(x, y) < "\infty$$

Equation 2.1 Non-zero and Infinite Quantity

Image Acquisition entirely depends on the system's hardware, which may include a sensor that is also a hardware device. A sensor converts light into electrical charges. The sensor of a camera detects the energy reflected by the captured scene. Most digital cameras use charge-coupled devices (CCDs) as image sensors [20]. Some cameras use complementary metal oxide semiconductor (CMOS) technology [20]. CMOS sensors often have a low power consumption. CCDs, on the other hand, utilize an energy-intensive procedure. CCDs can waste up to 100 times more energy than a comparable CMOS sensor. CCD sensors have been manufactured on a larger scale for a longer length of time, hence they are more mature. They often have higher quality and more pixels.

2. 4 Convolutional Neural Network

In the middle of the last century, the artificial neural network system was a groundbreaking discovery. It offers good, distributed data storage, parallel processing, self-organizing, and self-learning characteristics, and it is widely utilized. Convolutional neural networks are widely employed in a variety of industries, but researchers in the disciplines of processing information, pattern matching, adaptive control, and system modeling are particularly interested in them [21]. The convolutional neural network algorithm employs backpropagation techniques with learning samples as part of supervised learning. So that the output structure and the anticipated vector are indefinitely close, the network's deviance is repeatedly adjusted [22].

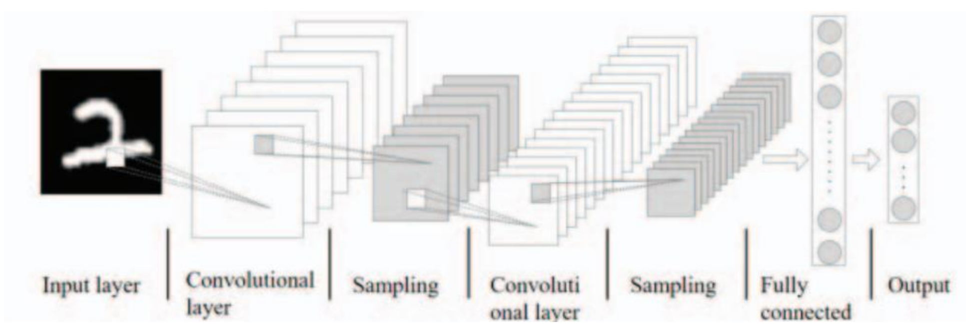

Figure 2. 3 Typical Structure of Convolutional Neural Network

Convolutional neural networks typically have the following layers: input, convolution, down-sampling (also known as pooling), completely connected, and output layers [23], which are shown in Figure 3. An approach to comprehending the nature and purpose of complex systems is through the study of complex networks, which concentrate on the structure of how people interact within systems. Regular networks, such as the Euclidean grid or closest neighbor network in the two-dimensional plane, were the starting point for studies of complex networks [24].

2.5 Canny Edge Detection

A Canny edge detector is a multi-step method that detects the image's edges. When detecting the edges of an image, the actions outlined below must be taken. Edge detection is not only the foundation for the detection of standard image primitives but also the initial step in edge-based image segmentation. One of the most fundamental characteristics of an image is its edge, which is the collection of pixels with abrupt changes in gray level[25].

In image processing, Canny, Laplacian of Gaussian, Sobel, Perwitt, and Roberts are used to detect edges[26]. The Canny edge detector is regarded as the most effective edge detection technology, capable of detecting weaker edges without being misled by image noise[27]. The method may identify weak edges by identifying points as edges if their amplitude is greater than that of their neighbors[28].

G(x,y) = (1/2ps 2)e^-(x2 +y2 /2s 2)

Equation 2.2 Gaussian Filter in Two Dimension

Where “s” is the Gaussian distribution's standard deviation, x is the distance from the origin in the horizontal direction, and y represents the distance in the vertical direction. Non-maximum suppression removes pixels that aren't edges, and only local maxima are designated as edges. By deleting non-edge pixels, a binary image with thinner edges results. Hysteresis thresholding is utilized to detect strong edges with gradient magnitudes over the upper threshold while pixels below the lower threshold are removed. Hysteresis thresholding detects weak edges related to strong edges. Moreover, by dividing the images into bit-planes, each bit-plane is subjected to Canny edge detection. This research differs from prior studies in this field since it analyzes bit-planes rather than the image itself [29].

The Canny algorithm contains some of the most optimal edge detection criteria.:

1) *Detect (detection criteria)*

The capacity to position and label all edges according to the selected convolution settings. While also offering a great deal of flexibility in setting the optimum edge thickness detection level.

2) *Localize well (localization criteria)*

Using Canny, it is feasible to determine the minimum distance between the detected edge and the original edge.

3) *Clear Response (response criteria)*

There is a single response for each edge, allowing further image processing to proceed without confusion. The choice of Canny edge detection parameters significantly impacts the results of the edges that are produced. The Gaussian standard deviation and the threshold value are examples of these parameters[30].

Additionally, the Canny algorithm marks a point as an edge if the amplitude is larger than its neighbors without checking that the differences are higher than expected[28]. This causes the algorithm to be sensitive to weak edges, such as where colors are similar or where the image is blurry. The Canny Edge algorithm proved a robust method in detecting fake bills through OVD security features, revealing a statistically significant detection proportion under a 5% level of significance.[31].

2.6 Hough Line Transformation

The Hough transform is a traditional technique for determining a line's properties in a binary image. Each picture point is mapped to every possible point in the parameter space by this transform, which was developed to find parameterized patterns in binary images [32]. Each image point then casts a vote for the shape parameters that could have given rise to it. The shape(s) in the actual image is most likely to have been formed by the point(s) in the parameter space receiving the greatest number of votes, which appear as peaks. As a result, the Hough transform reduces the challenge of locating localized peaks in the parameter space to that of detecting spatially dispersed patterns in the picture space [33].

$$\rho = xcos\theta + ysin\theta$$

Equation 2.3

where the distance from a point to a line and the angle between this line's normal and the x-axis, respectively, are denoted by the symbols. In other words, a curve in parameter space is mapped to the points in picture space [34]. At one point in the parameter, the point with the same parameter will meet a peak and prevent the area from changing, as depicted in Figure 2. The equations can view the lines from the original image by peak detection.

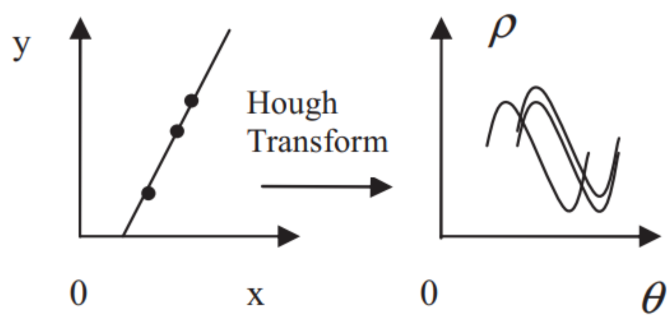

Figure 2. 4 Hough transform schematic

In the standard Hough transform (SHT), ρ and θ are specified as the parameter space, and (x, y) specifies the coordinates of the points on the straight line or the pixel space. The procedure determines whether any of the parameter bins (P ρ, θ) are sufficient proof that an actual line exists at that pixel, one that computes parameter values and acquires bins in the parameter space based on all pixels. The three steps of the conventional Hough transform computation are: (1) computing the parameter values and adding up the bins in the parameter space; (2) locating the local maxima that correspond to line segments; and (3) extracting the line segments using the information from the maximum positions. It makes one trip through the image's pixels. Since the total number of pixels, which is the sum of the image's width and height, is linear, its temporal complexity is also linear. The algorithm's storage needs also change with the number of pixels because it must gather each pixel's votes. Therefore, the typical Hough transform's primary bottlenecks are the computational complexity of the method and the storage needs. As a result, numerous modifications to the original Hough transform have been put forth to lessen the computational and storage strain [35].

The Hough transform (HT), which is resilient to noise and incomplete data, is a well-liked method for line detection. Software solutions have not been able to attain real-time performance, except for very small images, due to the computational expense associated with its voting method. There have been numerous dedicated hardware solutions put forth. However, their handling of various image sizes is constrained [36].

2.7 Optical Character Recognition

The method of classifying optical patterns within a digital image is known as optical character recognition (OCR). Segmentation, feature extraction, and classification are used to accomplish character recognition. The output of the OCR should ideally be the same as the input in formatting. The process involves some pre-processing of the image file and then the acquisition of important knowledge about written text[37].

OCR technology increases the productivity of office labor since, when performed effectively, the transformation permits searching electronic versions of documents that would otherwise be stored in filing cabinets, collecting dust. Because of this advantage of the OCR systems, they are employed in a wide area of banking[38]. Character recognition is one of the most interesting and fascinating areas of pattern recognition and artificial intelligence[39]. Character recognition has been getting more and more attention since the last decade due to its wide range of applications[40].

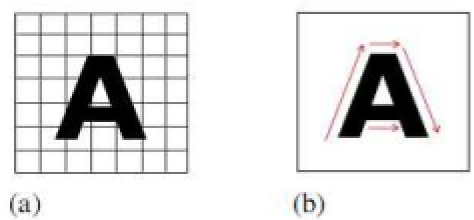

Figure 2. 5 Offline and Online Character Recognition

Systems can be classified as OCR or HCR, respectively. Online methods are superior to their counterparts, i.e., offline methods, due to the temporal information present in the character generation[41]. Various approaches are used for the design of OCR systems.

1) *Matrix Matching*

This technique describes each character based on the presence or absence of important characteristics, such as height, width, density, loops, lines, and stems. Feature extraction is the optimal OCR technique for magazines, laser print, and high-resolution photos.

2) *Fuzzy Logic*

Fuzzy logic is a multi-valued logic that permits the definition of intermediate values between traditional evaluations such as yes/no, true/false, black/white, etc. An attempt is made to imbue computer programming with a more human-like mode of logical thought. When uncertainty is present, fuzzy logic is employed when answers lack a distinct true or false value.

3) Feature Extraction

This technique describes each character based on the presence or absence of important characteristics, such as height, width, density, loops, lines, and stems. The feature extraction method is ideal for OCR of periodicals, laser prints, and high-resolution photos.

4) Structural Analysis

Analyzing the image's sub-vertical and horizontal histograms, Structural Analysis finds characters based on the image's geometry. Its capacity to fix characters is excellent for low-quality text and newsprints.

4) Neural Networks

This technique mimics the operation of the human nervous system. It takes a sample of each image's pixels and compares them to an index of character pixel patterns. Fax documents and damaged text benefit significantly from the capacity to recognize characters through abstraction. Neural networks are ideally suited for some tasks, such as analyzing stock market data and identifying trends in graphical patterns.

Micro-lettering can be detected using advanced OCR (Optical Character Recognition) techniques on an enhanced image. See-through register optically variable connection, security threads, intaglio printing, fluorescence, identification mark, and legal protections against counterfeiting are some of the techniques for identification implemented by many researchers[42].

2.8 Gaussian Mixture Model

Gaussian mixture models (GMMs) are employed to cluster data. GMMs are utilized to accomplish either hard or soft clustering on query data. The Gaussian mixture model (GMM) method segments an image into many objects[43]. This approach segments the image using n normal-Gaussian PDFs.

Additionally, to split the area of a histogram, modeling with a GMM is required. This method finds the gray histogram of an image and estimates a model that is most comparable to the histogram using the GMM[44]. Using the GMM, the following procedure is utilized to forecast a histogram with a mixture of k components. Given is the Gaussian mixture PDF with a mixture of k components.

The correlation coefficient measurement between the segmented and standard patterns revealed that GMM is ideally suited for separating the UV pattern and exhibited extremely high accuracy[44].

Chapter 3

METHODOLOGY

3.1 Conceptual Framework

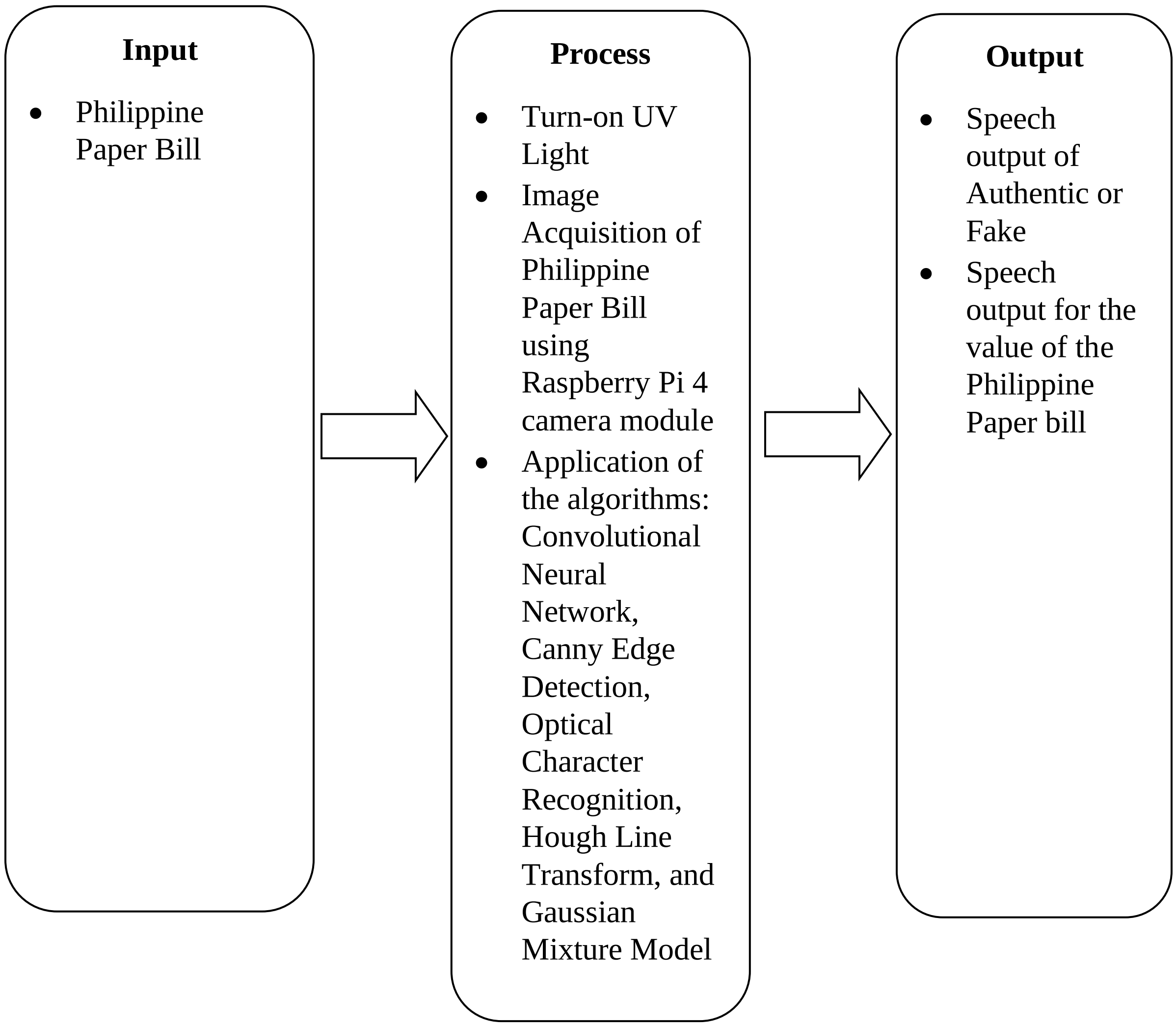

Figure 3. 1 Conceptual Framework

The input for the system will be the Philippine Paper Bill. The process is divided into three stages: (1) turning on the UV light in order to obtain the patterns on the paper bill. (2) The image acquisition using the microcontroller and a camera module. (3) The data extraction using algorithms like Convolutional Neural Network, Canny Edge Detection, Optical Character Recognition, Hough Line Transform, and Gaussian Mixture Model. Lastly, the system should identify whether the paper bill is authentic or not using a speech device and speaker.

3.2 System Process Flow

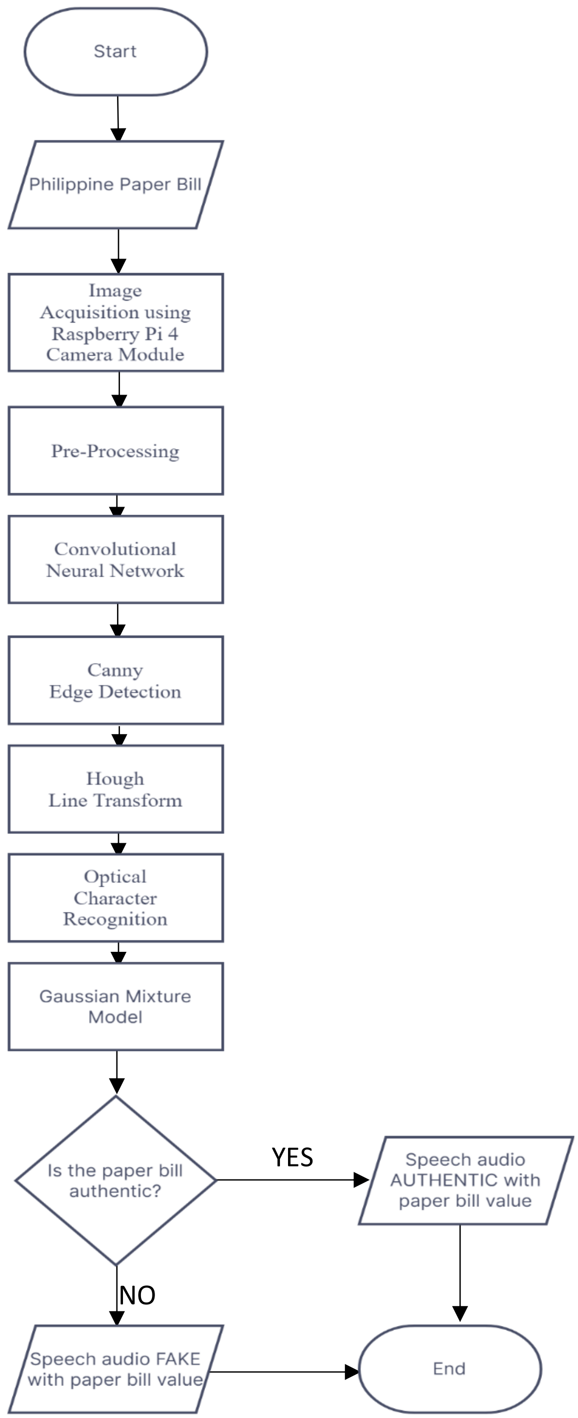

Figure 3. 2F System Process Flow Diagram

The design process of determining the authenticity of the Philippine paper bill starts with putting the paper bill in the place where the camera module is above. Once the paper bill has been placed, the camera module will start to acquire the features using the Raspberry Pi 4 Model B. The Raspberry Pi 4 Model B will undergo image processing techniques to extract the feature needed to obtain the authenticity of the paper bill. After extracting the data from the image processing algorithms, the audio device will announce whether the paper bill is authentic or fake.

3.3 List of Materials

1. Raspberry Pi 4 Model B

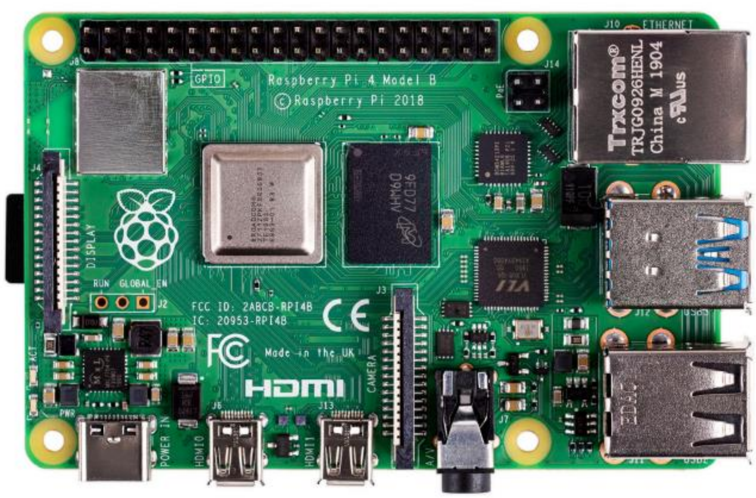

Figure 3. 3 Raspberry Pi 4 Model B

This product’s key features include a high-performance 64-bit quad-core processor, dual-display support at resolutions up to 4K via a pair of micro-HDMI ports, hardware video decode at up to 4Kp60, up to 8GB of RAM, dual-band 2.4/5.0 GHz wireless LAN, Bluetooth 5.0, Gigabit Ethernet, USB 3.0, and PoE capability (via a separate PoE HAT add-on).

2. Laptop

Figure 3. 4 Laptop

A laptop is a small and compact personal computer. This will be used to program the Raspberry Pi 4 Model B. It is also equipped with MATLAB software that will be used for image processing.

3. Raspberry Pi Camera Module 2

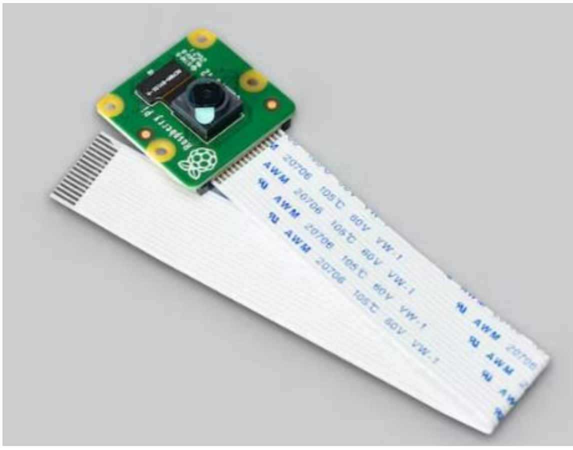

Figure 3. 5 Raspberry Pi Camera Module 2

The Raspberry Pi Camera Module 2 is equipped with an 8-megapixel sensor that can be used to take still photographs and high-definition video. This will be used to capture the image of the paper bill.

4. Ultraviolet (UV) Light Lamp

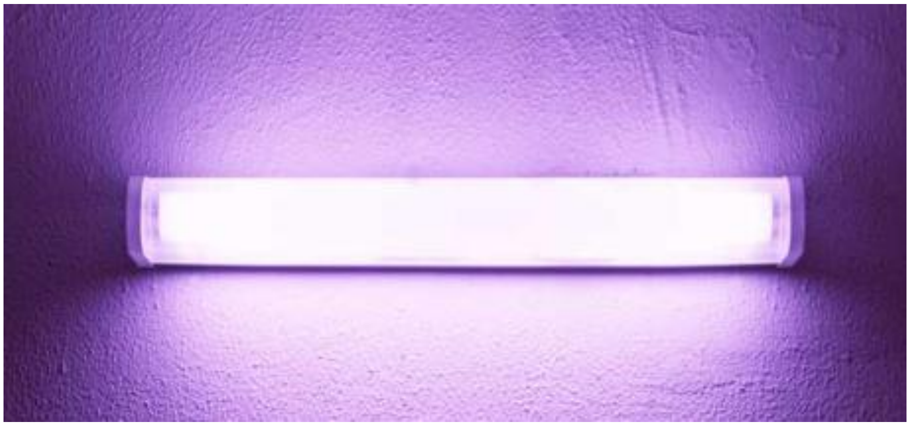

Figure 3. 6 Ultraviolet (UV) Light

The ultraviolet light lamp will be used in validating the watermarks and the level 2 security of the paper bill.

5. Speaker

Figure 3. 7 Speaker

The speaker will be used to output an audio prompt of the amount of the currency, its condition, and whether it is fake or authentic.

6. Sample Case

Figure 3. 8 Sample Case

The case will be used in assembling the parts of the project. The case will be portable so that it can be used on the go.

7. Push button

Figure 3. 9 Push Button

The push button will be used to start the authentication process of the paper bill.

7. Braille On and Off switch

Figure 3. 10 Braille On and Off switch

The user will use the switch to turn them on and off the device. The added braille will aid the visually impaired and blind people to know whether the device is turned on or off.

8. Power Supply

Figure 3. 11 Power Supply

A 5V 3A USB-C power supply that is designed for the Raspeberry Pi 4 model B will be used to power the device.

3.4 Proposed Concept Design of Prototype

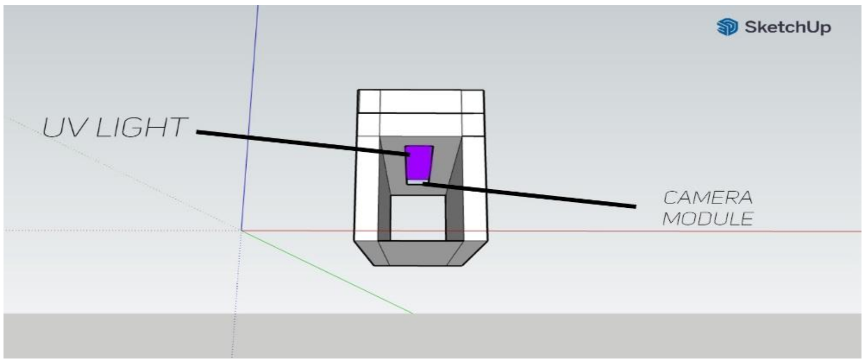

Figure 3. 12 Front View of the Prototype

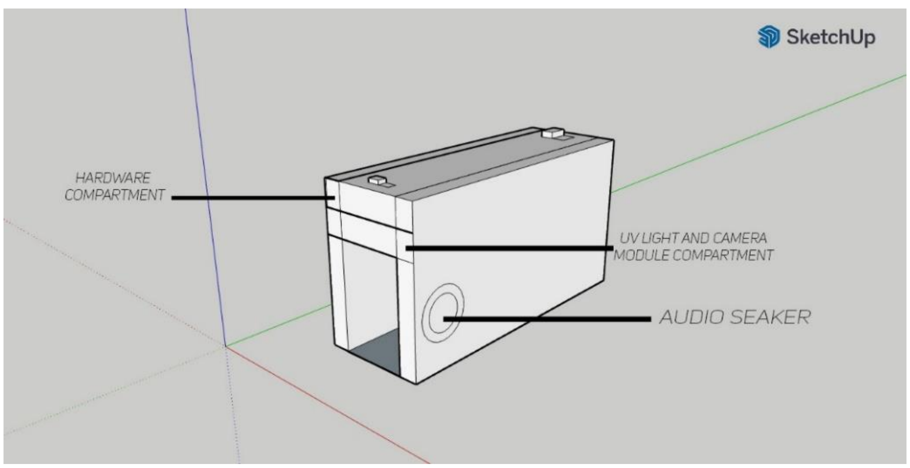

Figure 3. 13 Side View of the Prototype

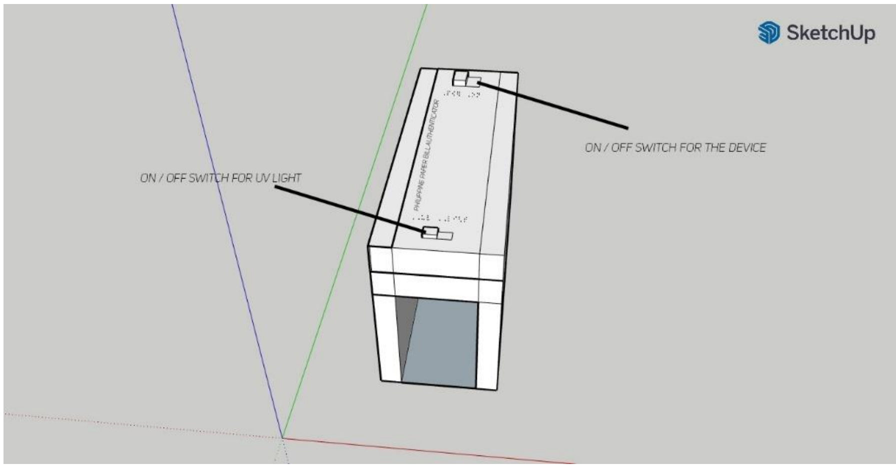

Figure 3. 14 Top View of the Prototype

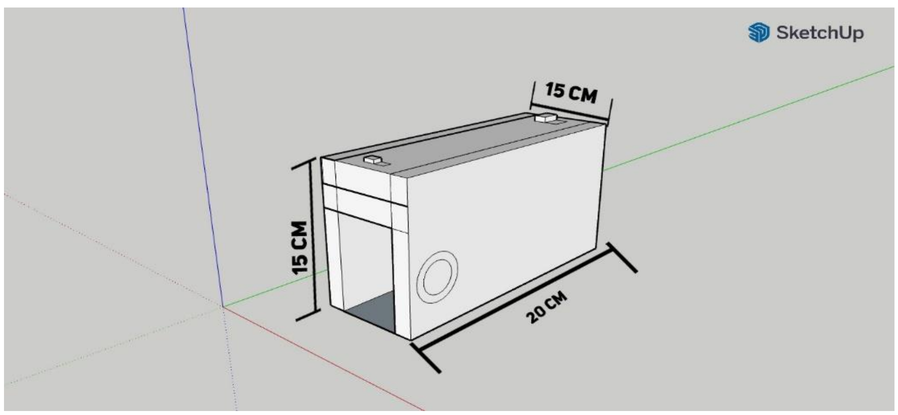

Figure 3. 15 Dimension of the Prototype

The prototype will be made of 3D-printed plastic material that can fit the device's hardware, UV light, and camera module. Figure 3.12 is the front view of the device. It consists of the entrance where to put the money in the device, the UV light that will make the invisible marks of the money visible, and the camera module that will acquire the specifications and pieces of information about the money to the hardware.

Figure 3.13 shows the compartment of the UV light, camera module, and the Raspberry Pi 4 Model B. The audio speaker will be on the side of the device, where the device will tell the user if the money is fake or authentic.

The third figure is the top view of the prototype, where there is a push button to activate the hardware and the UV light. Since this is for the visually impaired person, it has labels in braille that can help navigate the switch button for the UV light and the device.

Figure 3.15 explains the dimensions of the device. The dimensions are based on the calibration and the size of the hardware. The dimensions are 15 centimeters in height, 20 centimeters in length, and 15 centimeters for the device's width.

3.5 Data Gathering

Objective 1: to design a Philippine paper bill authenticator for the blind that detects level 1 and level 2 security features

1. *Experiment Setup*

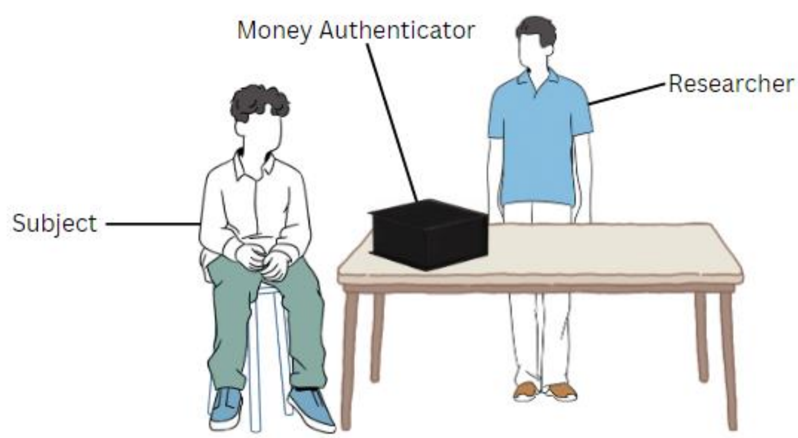

Figure 3. 16 Experiment setup

Figure 3.16 shows the experiment setup. The device and the subject are the basic components that compromise the system. The testing and gathering of data are carried out in a controlled setting to guarantee consistency. The subject can be either standing up or sitting down. The setup begins when the subject is handed some paper bills. The experiment will use one authentic paper bill and one fake paper bill of each denomination. The device only scans one paper bill at a time. Since the subject is blind or visually impaired, placing the device on a flat surface is recommended after putting it out of the bag to prevent damaging or breaking the device. The subject should plug in the device using the power supply and turn on the device by sliding the switch from off to on to start working. The device will audio prompt a message that the device is now turned on and switch on the UV light. Switch the UV light switch from off to on; this audio prompts a message that the UV light is turned on and place the paper bill in the dedicated slot, then press the start button. Pressing the start button on the device will audio prompt a message saying the device is scanning, indicating the device is currently scanning the paper bill. If the paper bill is not correctly placed on the device, the device will do an audio prompt message that says the money is set incorrectly. The subject should reposition the paper bill by flipping or placing it correctly on the dedicated slot on the device and pressing the start button again. When the bill is positioned correctly, the device will continue to scan the paper bill and will audio prompt a message if the paper bill is authentic or fake, its amount, and the paper bill is now ready to be removed. The subject can now get the paper bill on the device after the authentication procedure and repeat the process when doing another authentication. After using the device, switch the UV light switch from on to off, and this audio prompts a message that the UV light is now turned off, and switch the power switch from on to off audio prompts a message that the device is now turning off.

	Php 20 Paper Bill	*Php 50 Paper Bill*	*Php 100 Paper Bill*	*Php 200 Paper Bill*	*Php 500 Paper Bill*	*Php 1000 Paper Bill*
Accuracy						
Error Rate						

Sensitivity	
Specificity	
Precision	
False Positive Rate	

Table 3. 1 Evaluating the System

$$Accuracy = \frac{TP + TN}{P + N}$$

$$Error\ Rate = \frac{FP+FN}{P+N}$$

$$Sensitivity = \frac{TP}{TP+FN}$$

$$True\ Negative\ Rate = \frac{TN}{TN+FP}$$

$$Precision = \frac{TP}{TP+FP}$$

$$False\ Positive\ Rate = 1 - True\ Negative$$

Equation 3.1 Formula of Accuracy, Error Rate, Sensitivity, True Negative Rate, Precision, and False Positive Rate

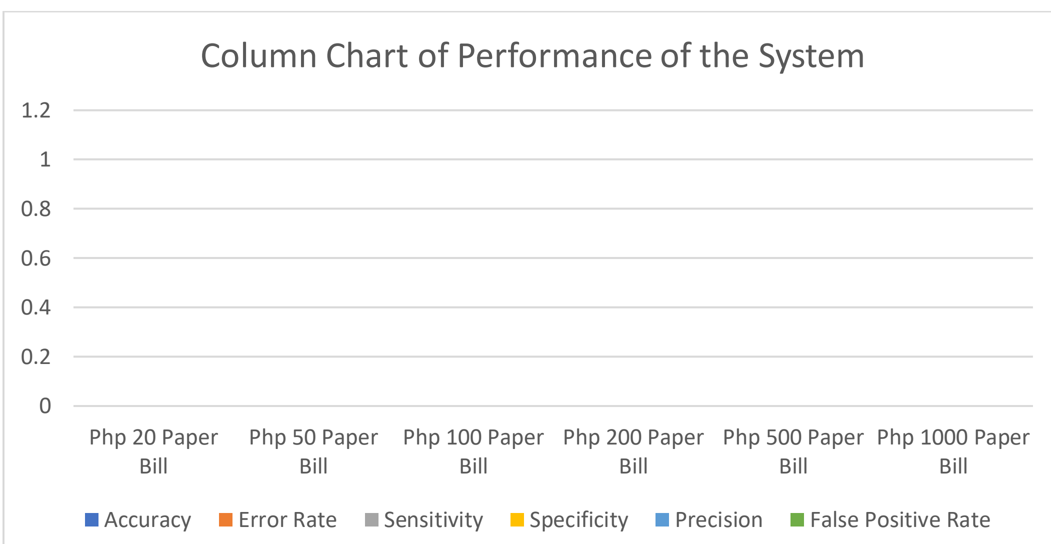

Figure 3. 17 Column Chart for Performance of the System

In testing the device's functionality, the researchers will test 1 authentic and 1 fake for each paper bill from 20-peso bill to 1000 peso-bill. Table 3.1 will show and evaluate the system's performance. The system's performance will be based on the Accuracy, Error Rate, Sensitivity, Specificity, Precision, and False Positive Rate.

Test No.	Test Case	Expected Detection Output	Detection Output
1	₱20	100%	
2	₱20	100%	
3	₱20	100%	
4	₱20	100%	
5	₱20	100%	
		Mean Average	

Table 3. 2 Testing of ₱20 Bill

Table 3.2 shows the testing of the ₱20 paper bill

Test No.	Test Case	Expected Detection Output	Detection Output
1	₱50	100%	
2	₱50	100%	
3	₱50	100%	
4	₱50	100%	
5	₱50	100%	
		Mean Average	

Table 3. 3 Testing of ₱50 Bill

Table 3.3 shows the testing of the ₱50 paper bill

Test No.	Test Case	Expected Detection Output	Detection Output
1	₱100	100%	
2	₱100	100%	
3	₱100	100%	
4	₱100	100%	
5	₱100	100%	
		Mean Average	

Table 3. 4 Testing of ₱100 Bill

Table 3.4 shows the testing of the ₱100 paper bill

Test No.	Test Case	Expected Detection Output	Detection Output
1	₱200	100%	
2	₱200	100%	
3	₱200	100%	
4	₱200	100%	
5	₱200	100%	
		Mean Average	

Table 3. 5 Testing of ₱200 Bill

Table 3.5 shows the testing of the ₱200 paper bill

Test No.	Test Case	Expected Detection Output	Detection Output
1	₱500	100%	
2	₱500	100%	
3	₱500	100%	
4	₱500	100%	

5	₱500	100%	
		Mean Average	

Table 3. 6 Testing of ₱500 Bill

Table 3.6 shows the testing of the ₱500 paper bill

Test No.	Test Case	Expected Detection Output	Detection Output
1	₱1000	100%	
2	₱1000	100%	
3	₱1000	100%	
4	₱1000	100%	
5	₱1000	100%	
		Mean Average	

Table 3. 7 Testing of ₱1000 Bill

Table 3.7 shows the testing of the ₱1000 paper bill

Ratings about the experience using the device (Very Unsatisfied, Unsatisfied, Neutral, Satisfied, Very Satisfied)	
Device Accuracy	
Device Design	
Device Convenience	
Purpose of the Device	
Device Performance	

Encountered Error (Please Specify)	
How is the experience when you are using the device?	

Table 3. 8 Feedback Questions from the Subject

Table 3.8 will show the feedback from the subject based on their experiences when using the device. The results from the feedback will be used to evaluate the system. The result will be based on the subject's satisfaction and will be used to improve the device further. The outcome of the survey will use take further improvement of the device.

2. *Hardware*

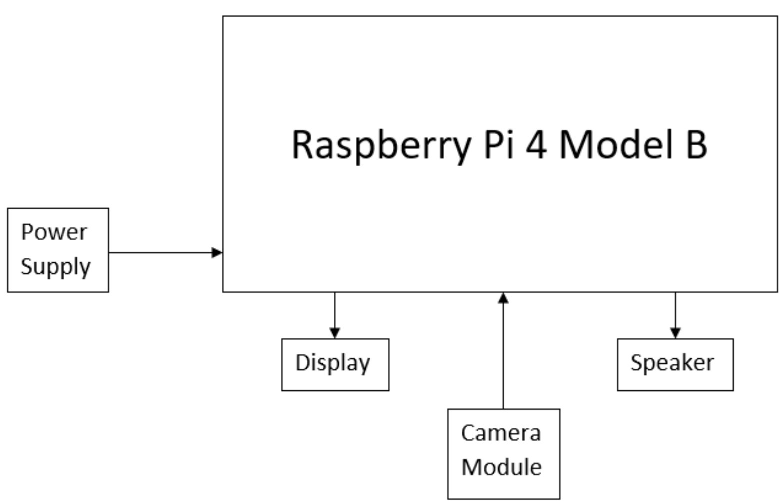

Figure 3. 18 Block Diagram of the Raspberry Pi 4 Model B

Figure 3.18 shows the block diagram of the Raspberry Pi 4 Model B. The hardware of the device contains a push button that will turn the system on and off, a speaker for the narration of the authenticity of the Philippine peso bill, and a camera module that will acquire the model of the Philippine peso bill.

3. Calibration

No. of Test	Height (cm)	Remarks
1	3	
2	6	
3	9	
4	12	
5	15	

Table 3. 9 Calibration of Camera Height

Table 3.9 shows the calibration of the camera's height from the paper bill. The researchers plan to have five trials; the first trial will start at 3cm up to 15cm with a step of 3cm until the researchers obtain a clear and unblurred image. The camera's height will be determined by the clearest image captured after gathering and reviewing the results. The remarks will be on how the money is seen at a specific camera height and if the paper bill's features are clearly captured. The placement of the light also at the compartment of the camera module.

The parameters will be set after capturing and importing high-quality raw images of each paper bill and used as a template for testing each paper bill. We will use only one sample of an authentic banknote for each denomination because it already has the required features to be calibrated for authenticating a paper bill. The use of Canny

Edge Detection will make the detection of the paper bills features because it removes unnecessary images on the paper bill. The Hough Line Transformation will reduce the image to the security thread area and exclude unwanted features from the image of the paper bill. Also, using Gaussian Mixture Models identify UV patterns and organize them necessary for the actual patterns.

4. *Classification of Authenticity*

Figure 3. 19 New Generation Currency Notes

Figure 3.19 shows the generation currency note of the Philippines. Currency must incorporate more outstanding anti-counterfeiting capabilities. The banknotizer, a highly trained artist in currency design, must modify the layouts completed by the Filipino artists to add security measures without compromising the original design concept. The new characteristics of the NGC notes were created so that regular cash handlers could quickly identify the legitimacy of each denomination while making it difficult and costly for counterfeiters to replicate.

Figure 3. 20 Example of Fake Money

Figure 3.20 shows actual fake money that will use in testing if the device can detect fake money. Obtaining fake money has many laws to be followed. For example, if someone uses fake money, he can be detained for months. To test fake money, the researchers will print fake money or buy play money. After taking the fake money to a test, the researchers should burn the example of fake money. In another way, the researchers will find fake money used in a pawnshop or store. The researchers ensure that the fake money will only be used to test the device.

Level 1 Security

Figure 3. 21 Level 1 Security Features of a Philippine Peso Bill

Figure 3.21 shows the level 1 security features of a banknote. The general population may readily identify features of security without the need for specialized equipment. The authenticity of a banknote can be justified by the following: asymmetric serial number, security fibers, watermark, see-through mark, concealed value, security thread, optical variable device, and optically variable ink.

Level 2 Security

Figure 3. 22 Level 2 Security Features of a Philippine Peso Bill using UV Light (Front)

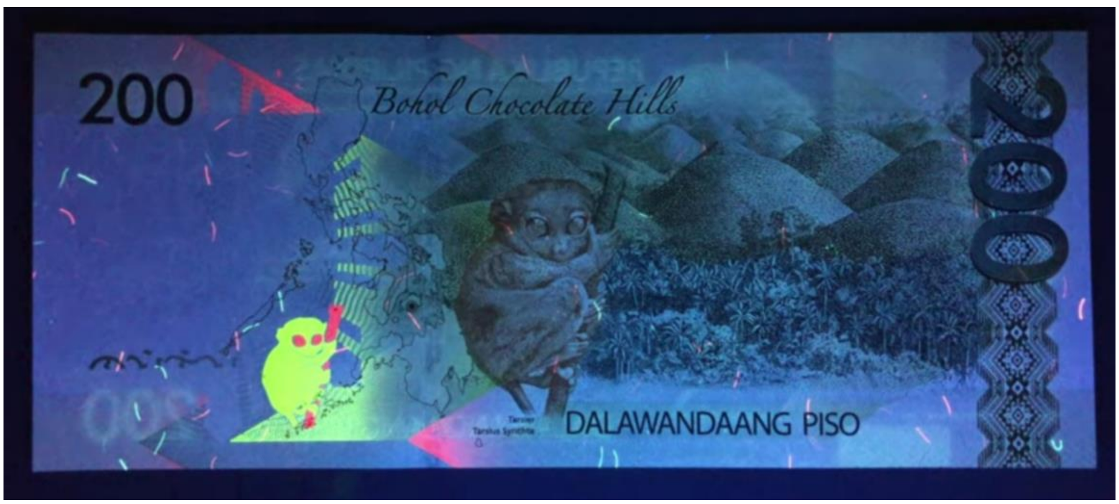

Figure 3. 23F Level 2 Security Features of a Philippine Peso Bill using UV Light (Back)

Figure 3.22 and 3.23 show a sample level 2 security feature of a Philippine banknote under a UV light. Bank tellers can see the security features using a magnifying glass or UV light. The authenticity of the banknote using a UV light can be determined by the following: In the front, there will be a security number and some fiber that can be seen only in UV light. For the back, a figure similar to the design at the back will be and some fibers.

3.6 Algorithms

Objective 2: to utilize different algorithms such as Convolutional Neural Network, Canny Edge detection, Hough Line Transform, Optical Character Recognition, and Gaussian mixture model that will detect the level 1 and level 2 security features of Philippine currency

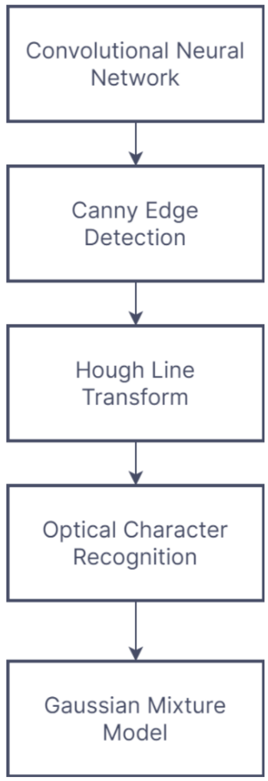

Figure 3. 24 Image Processing Techniques

1. *Convolutional Neural Network*

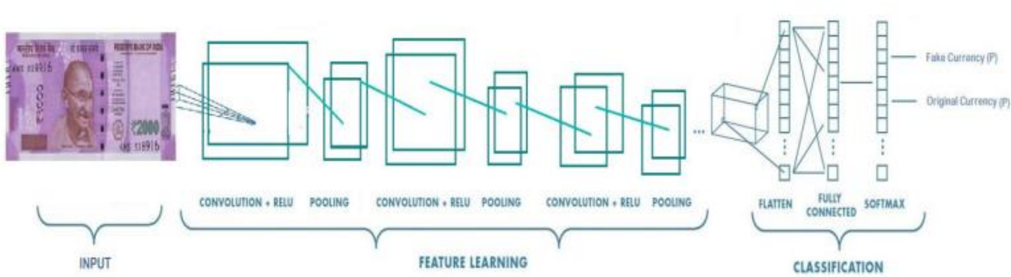

Figure 3. 25 Process of Convolutional Neural Network

The system's image segmentation procedure can separate the image into its constituent pieces. The segmented photos will be shown according to the algorithms used to get the feature. CNN functions as a feature extractor, obviating the requirement to perform image processing techniques and manually examine the existence of security characteristics on a note. For the system to recognize the watermark, the researcher will employ the Convolutional Neural Network threshold. CNN improves picture quality and aids in boosting the resolution of the ancient manuscript.

2. *Canny Edge Detection*

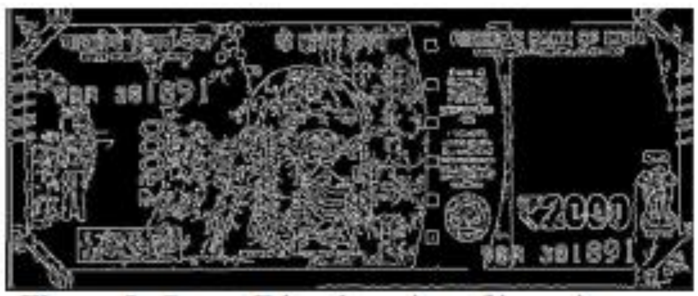

Figure 3. 26 Canny Edge Detection of sample input image

Pre-processing of the Canny Edge eliminates extraneous images found on banknotes, making recognizing banknote characteristics far simpler. Canny Edge Detection will be utilized to recognize and map the banknote's edges. For calibration, a BGR picture of the banknote was converted to a monochrome image with a white line representing the detected edges. Canny Edge Detection will be utilized to recognize and map the banknote's edges. For calibration, a BGR picture of the banknote will be converted to a monochrome image with a white line representing the detected edges.

3. Hough Line Transform

Figure 3. 27 Image Registered using Hough Line Transform

Hough Line Transformation will shrink the picture to the location of the security thread and eliminate any unwanted images from the banknote, making the identification of the banknote characteristics more straightforward.

4. Optical Character Recognition

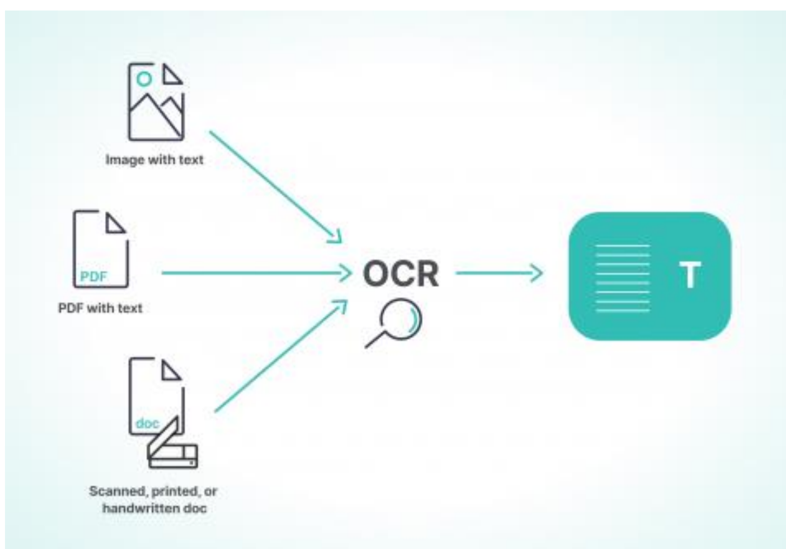

Figure 3. 28 Optical Character Recognition

The Optical Character Recognition will be utilized to recognize the characters existing on the banknotes. OCR operates by storing as templates several typeface and text picture patterns. The serial number is calibrated using the same settings as Canny edge Detection, and the serial number identified by Canny edge is converted to a string using Tesseract OCR. Incorporating Tesseract OCR is intended to recognize the image's data and translate it into a string. If it fits the parameter's template set, the serial number is determined. The algorithm correctly identified the feature since it matched the predetermined template.

5. *Gaussian Mixture Model*

Figure 3. 29 Image segmentation of UV-image using GMM

Gaussian Mixture Models may identify complicated patterns and organize them into cohesive, homogenous components that are close approximations of the data set's actual patterns. To split the region of a histogram, modeling with a GMM is required. This approach identifies the gray histogram of an image and estimates a model that is most comparable to the histogram using the GMM [44]. By measuring the correlation coefficient between the segmented pattern and the standard pattern, the accuracy of this approach for separating the UV pattern was determined to be extremely high.

3.7 Audio Prompt Device

Objective 3: to add an audio prompt element that can assist visually challenged individuals in the counterfeit detection.

The device will output an audio prompt on the value of the paper bill and if it is authentic or fake to aid the need of the visually impaired and blind people in authenticating their money. The audio prompt device is a built in speaker that is loud enough for the user to hear the output in an outside environment. The built in speaker is attached through an auxiliary cord in the AUX slot of the Raspberry Pi microprocessor.

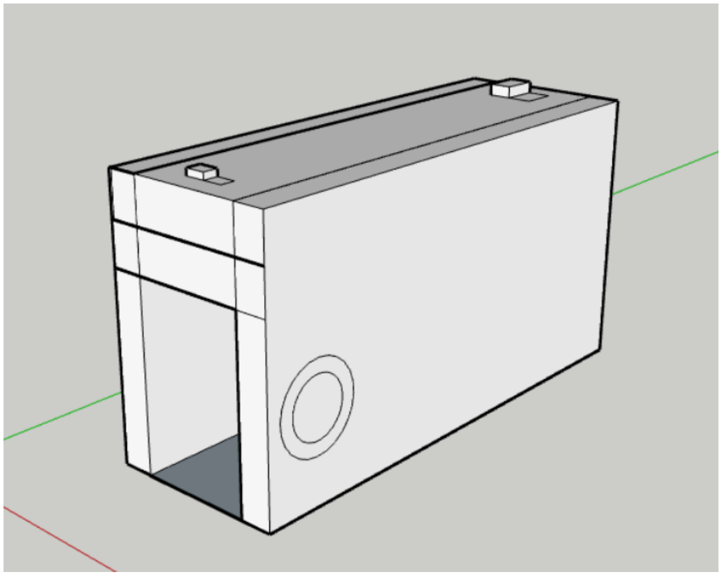

Figure 3. 30 Built-in speaker in the device

The figure shows the built-in speaker at the side of the device where the audio prompt will be outputted. From the start of the device, the subject will hear instructions on how to put the money on the device. At the end of using the device, they will hear the paper bills' output value and whether they are authentic.

3.8 Confusion Matrix

Objective 4: utilizing confusion matrix to validate the accuracy and functionality of the device for each currency.

N=	Predicted: authentic	Predicted: fake
Actual: authentic	TN =	FP =
Actual: fake	FN =	TP =

Table 3. 10 Confusion Matrix for 20 Philippine Peso Bill

N=	Predicted: authentic	Predicted: fake
Actual: authentic	TN =	FP =
Actual: fake	FN =	TP =

Table 3. 11 Confusion Matrix for 50 Philippine Peso Bill

N=	Predicted: authentic	Predicted: fake
Actual: authentic	TN =	FP =
Actual: fake	FN =	TP =

Table 3. 12 Confusion Matrix for 100 Philippine Peso Bill

N=	Predicted: authentic	Predicted: fake
Actual: authentic	TN =	FP =
Actual: fake	FN =	TP =

Table 3. 13 Confusion Matrix for 200 Philippine Peso Bill

N=	Predicted: authentic	Predicted: fake
Actual: authentic	TN =	FP =
Actual: fake	FN =	TP =

Table 3. 14 Confusion Matrix for 500 Philippine Peso Bill

N=	Predicted: authentic	Predicted: fake
Actual: authentic	TN =	FP =
Actual: fake	FN =	TP =

Table 3. 15 Confusion Matrix for 1000 Philippine Peso Bill

To verify the reliability of the trial data, it is compared against six confusion matrices, one for each denomination of banknote, shown in the table above, where each matrix has four possible outcomes.

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