An Application of Image Processing Technology in Counting Rebars as an Alternative to Manual Counting Process

Mikale Rizton Ablidas [1], Armil Monsura [1], Lhora Anne Ablidas [2], Jesse Dela Cruz [1]

[1] College of Engineering, National University, Manila, Philippines.
[2] *Computer Engineering Department*, Technological Institute of the Philippines, Quezon City, Philippines.

Email: mrmablidas@national-u.edu.ph; asmonsura@national-u.edu.ph; lam.ablidas@gmail.com; jessedelacruz22@gmail.com

Abstract **- Error in manual counting of reinforcement bars (rebars) is one of multiple concerns that may happen in steel bar rolling mills that necessitate double checking in warehouses and delivery areas. Numerous steel bar rolling mills manually count rebars in their packaging line. This process is susceptible to errors because of low human work efficiency. This led the researchers to study an alternative way of counting rebars with higher accuracy. It uses image processing with K-means algorithm and Hough transform. The proposed system can validate and check the rebar quantity in a bundle. The study used waterfall and prototype models in the development of the system and goodness of fit test to check its effectiveness. The test was conducted on a typical rebar rolling mill packaging line. For a sample size of 41 and 0.05 significance level, the obtained results were: critical test statistic = 55.76, test statistic = 0.0553 and the probability value = 0.99. This shows that there is no significant difference between the results of counting using the proposed system and expected standard rebar quantity in a bundle. Analysis of the duration of counting using both methods also reveal significant difference favoring the proposed system. Furthermore, the time saved were vast when there were more rebars in a bundle. Overall, the study demonstrated that the proposed system is an efficient way of counting rebars.**

Keywords - Steel bar rolling mill, Rebar, Image processing, k-means algorithm, Hough transform

I. INTRODUCTION

In the manufacturing industry, one of the important processes in packaging is product counting. This process determines the required number of products to be placed in its final containment or enclosure. In recent years, incorrect product quantity is considered by many companies as one of the issues that need to be prevented because of the effect it can introduce to the customers. Some of its possible effects include double handling of products, excessive recounting, delays in delivery, and waste of time both for company and its customers. Because of this, systematic procedures and processes involving the use of technology in counting products are being sought. According to [1], delivering correct quantity of products to the consumer is one of the main objectives in commercial transactions. An improvement on packaging system, mainly on product counting process, will play a vital role in achieving this objective.

In steel bar rolling mill, systems that use photoelectric cells and manual counting are the common methods used in determining the quantity of rebars [2]. The success of counting rebars using photoelectric cell relies on the position of rebar in the packing bed. The key for this process to work is by ensuring that there is a gap between consecutive rebars. The rebars' position is uncontrollable making it difficult to detect. On the other hand, manual counting is highly susceptible to error. Manual counting cannot meet the real-time requirements of online counting because of high worker labor intensity, low work efficiency and not matching the speed of chain bed; thus, they become speed bottlenecks in automated steel production process. The process is very unreliable – it introduces more error and requires higher man-hours [3]. Furthermore, the administrative controls in place, such as redundant checking provide inconsistent results, aside from adding more man-hours. Because of these problems, the researchers propose image processing technology as an alternative solution to the rebar counting problem.

Numerous researches regarding product counting were based on image processing. The design of these systems, however, were very particular on the product they count. In most cases, the effect of the natural background of the products were not considered; some come-up with a pre-determined background to simplify their methods. This paper aims to develop image processing-based rebar counter that applies to any background and improve the counting method using k-means algorithm and Hough transform. The researchers intend to address the problem of having a bundle of incorrectly counted rebars leave the packaging line by integrating the proposed system in the process.

The system first recognizes the presence of bundled rebars. It then acquires a cross-sectional end image of bundled rebars using CMOS (complementary metal oxide semiconductor) camera. The rebars' image is isolated from the background, and the number of rebars detected is determined. A graphical user interface shows and records the output of the system, and an alarm system is put in place to detect and warn the user whenever errors in quantity are detected.

The system is seen to improve the process by making bundles of accurate number of rebars and by reducing the manpower the old process requires. It also simplifies the checking and validation processes of products leaving the packaging line. The system can count rebars after it is bundled. It can be implemented to all available diameters and lengths of rebars that are manufactured in a typical rebar rolling mill, except for 10 mm and 12mm.

II. REVIEW OF RELATED LITERATURE

A. *Steel Bar Rolling Mill*

According to [4], rolling, under the forming and shaping manufacturing process which accounts for about 90% of all metals produced by metalworking processes, was developed during the 1500s. Rolling is the most rapid method of forming metals into desired shapes by plastic deformation through compressive stresses using two or more than two rolls [5]. There are many products manufactured by means of rolling, and one of them is reinforcement bar. As mentioned in [5], continuous rolling mill consists of a number of non-reversing two-high rolling mills arranged one after the other, so that the material can be passed through all of them in sequence. It added that, two high rolling mill has two rolls revolving at the same speed but in opposite direction while three high rolling mill consists of three parallel rolls arranged one above the other.

B. *Packaging Section*

The packaging of rebar products in most plants is performed according to standard practices or special practices as required by the customer. Standard practices are controlled by such factors as the weight of the bundle or lift, the means of binding or fastening the bundles or lifts, the means of identification, the means of protecting the product in transit, and the geographical location of the customer. The quantity of rebars is also considered because it is used to validate the mass variation of the rebar. Acquiring the correct quantity of rebars in a bundle will lead to correct calculation of mass variation to recheck if the rebars are within the specified quality. Also, delivering correct quantity of rebars is of utmost importance both to the company and to the customers.

Some companies implement preventive and corrective actions to minimize the occurrence of shorts in delivered rebars. These actions mostly require manual rechecking of quantities before and after delivery, the use of global positioning system to monitor delivery trucks, and re-counting if the delivery seems underweight. These also led the companies develop protocols in cases of delivery abnormality. In the case of a short, a warehouse checker goes to the site to check. Affected trucks are untouched, pictures are taken, and interviews are made until both the supplier and the customer agree to and implement a solution. These actions are more of administrative controls and involve human intervention – thus more man-hours. They also cause delays and inconveniences both on the supplier side and the customer side. Supplier-customer trust can erode if this happens frequently. Applying a manufacturing-side preventive action is seen to eliminate most of the problems encountered whenever there are errors in the counting of rebars.

C. *Image Segmentation using Machine Vision*

In the context of machine vision, image segmentation is the task of finding groups of pixels that “go together”. Various algorithms are used in segmenting images. They include the thresholding method, edge-based method, region- based method, clustering method, watershed method, partial differential-based method and artificial neural network-based method. Table I shows the comparison of various segmentation techniques [6].

Among the segmentation algorithms listed, k-means clustering was chosen over the other algorithm because the former gave a more promising result than the others – that is, rebars are better isolated using k-means clustering.

TABLE I. COMPARISON OF VARIOUS SE GMENTATION TECHNIQUES

Segmentation Technique	Description	Advantage	Disadvantage
thresholding method	Based on the histogram peaks of the image to find particular thershold	No need of previous inforamation, simplest method	High dependent on peaks, spatial details are not considered
Edge based method	Based on discontinuity	Good for images having better contrast between objects	Not Suitable fro wrong detected or too many edges
Region based method	Based on partitioning image into homogeneous regions	More immune to noise, useful when it is easy to define similarity criteria	Expensive method in terms of time and memory
Clustering method	Based on homogeneous clusters	fuzzy uses partial membership therefore more useful for real problems	Determining membership function is not easy
watershed method	Based on the topological interpretation	Results are more stable, detected boundaries are continuous	Complex calculation of gradients
PDE based method	Based on the working differential equations	Fastest method, best for time critical applications	More computational complexity
ANN based method	Based on the simulation of learning process for decision making	no need to write complex programs	More wastage of time in training

III. METHODOLOGY

A. Conceptual Framework

The model used is based on the evaluation model of Daniel L. Stufflebeam's Input, Process and Product which is shown in figure 1. The image of bundled rebars is the input to the proposed system. The output will be the quantity of rebars and alarm if there is an error in quantity as compared to the standard quantity.

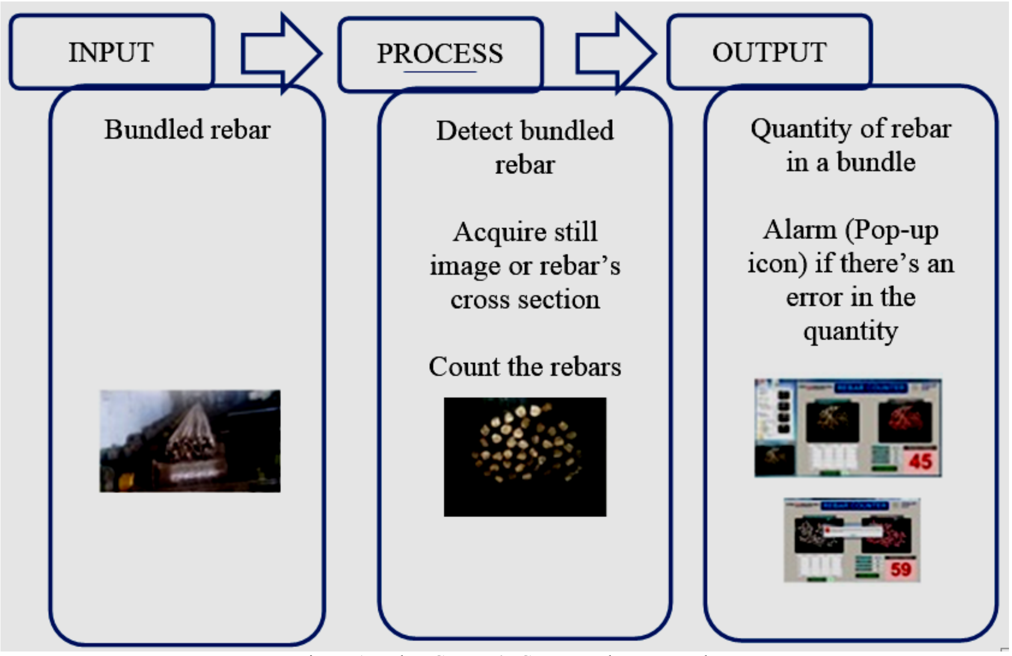

Figure 1. Rebar Counter's Conceptual Framework

B. Flow Chart of Rebar Counter

The system flow chart in figure II shows how system will ensure correct rebar quantity in a bundle. The system's functions are image acquisition, image processing and validation of the result. Each section is discussed in order to have a clear understanding on their functions. The discussion on each function focuses on the sequential process in order to achieve the desired objective.

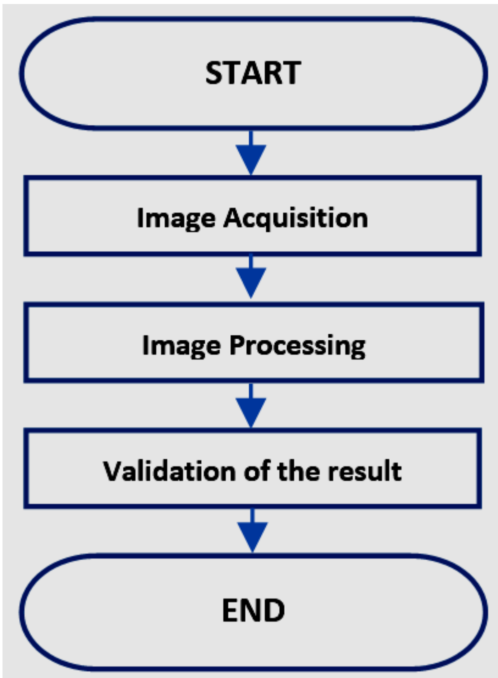

Figure 2. System Flow Chart

B.1. Image Acquisition

The packaging personnel will input the rebar's diameter, length and expected quantity in bundle on the GUI shown in figure III. The expected quantity will be compared to the output of the system. The system will start by acquiring cross sectional end image of bundled rebars in the packaging line shown in figure IV. After the weighing process, the bundle of rebars is moved to the bundled stock table waiting to be detected by the camera. When the camera detects it, this is the time where the cross-sectional end image of bundled rebar is taken and transmitted to the PC as an input to the proposed system. The flowchart is shown in figure 5.

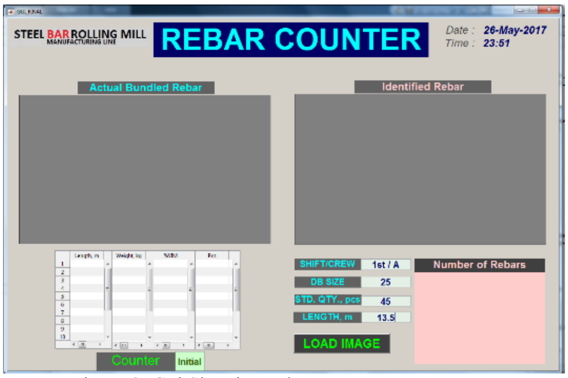

Figure 3. Gui Showing Where To Input Parameters

Figure 4. Image of Bundled Rebars; Input to the System

B.2. Image Processing

The heart of rebar counter is this section, where the input image is processed to identify the number of rebars in a bundle. The first process is color image masking. This process creates a pre-defined boundary to the rebar's image and its background. The color of area outside the rebar's image will be converted in black. The size of pre-defined boundary will be determined experimentally for every diameter and length of bundled rebars. This process will help the next process to effectively acquire the rebar's image. The output image after color image masking is shown in figure 6.

The second process is color segmentation using K-means algorithm. This process will isolate the rebar's image from the remaining background image. This will create three clustered images with different cluster center value. Two of the clustered images are the rebar's image. The clustered center value of rebar's image will be identified experimentally and be included in this process. The identified center value of rebar's image will be used to always get the clustered rebar's image. The three clustered images are shown in figure 8.

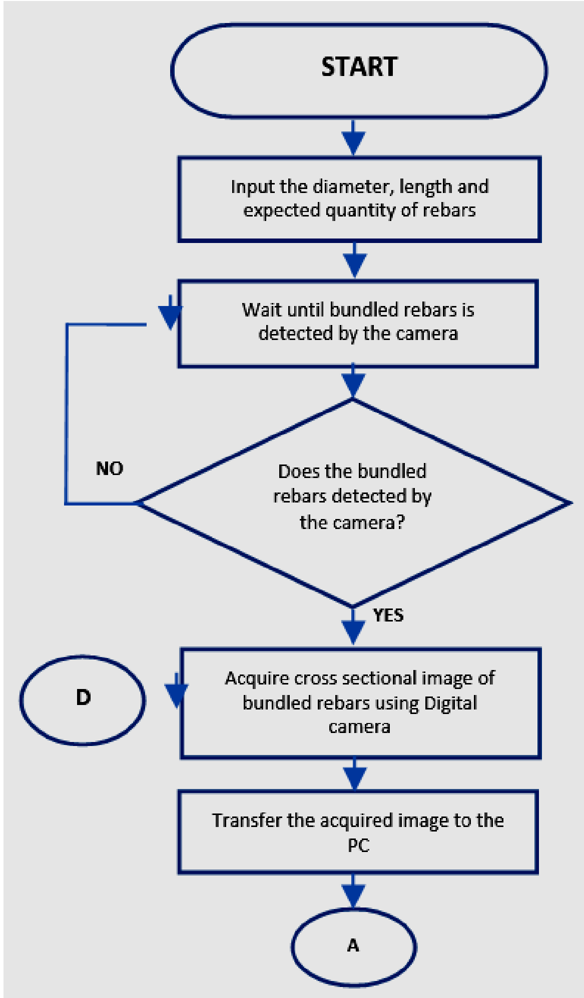

Figure 5. Image Acquisition's Flow Chart

Figure 6. Output Image after Color Image Masking

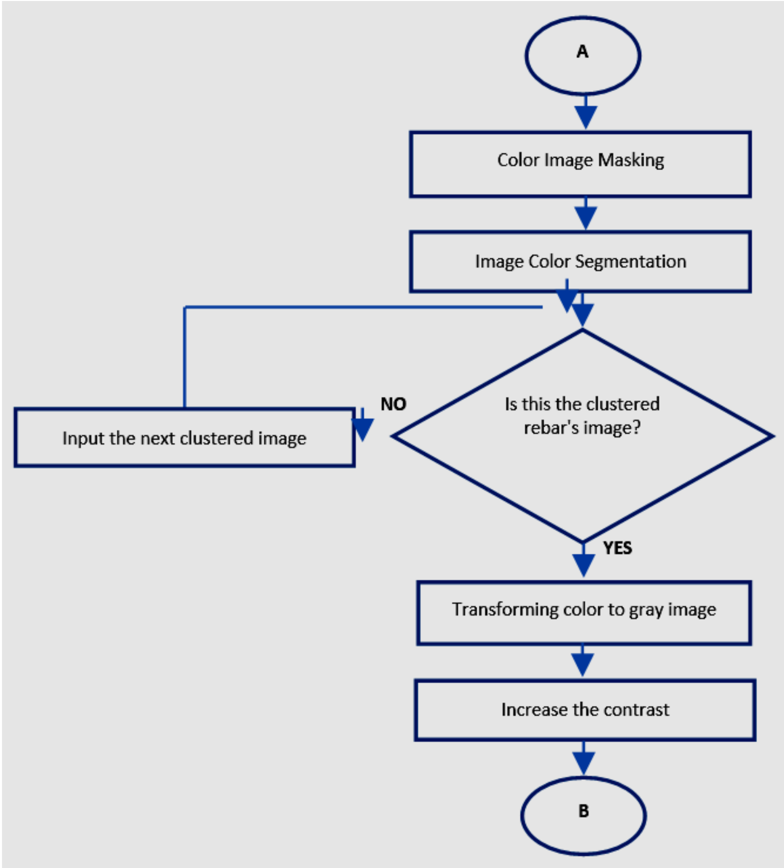

Figure 7. Image Processing Flow Chart A

The next process is the transformation of color image to gray. Most of the image processing operations are in the gray image. This gray image will be used in the next process. Next will be the enhancement of gray image through increasing the contrast and noise filtering using median filter. These output images after these processes are shown in figure 4, 5, and 6 respectively. The counting process will involve Hough transform to identify the bright circles and count it. This is shown in figure 13. If there are overlapped circles, the overlapped circles will be removed and retained the correct circle. This is shown in figure 12. The researchers used removeoverlap and snip Matlab function which are created by [7] and [8] in order to remove the unwanted circles. The said functions are available at Matlab file exchange site. After the circle has been counted, the result will be displayed on the GUI provided. The flowchart of image processing is shown in figure VII and figure 14.

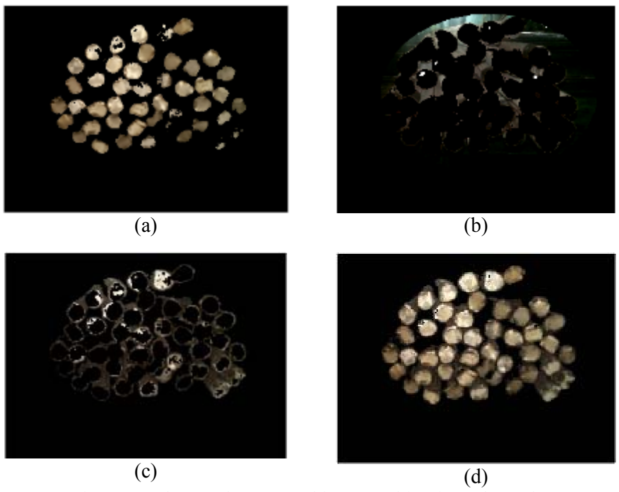

Figure 8. Clustered Images: d is a Combination of a and c

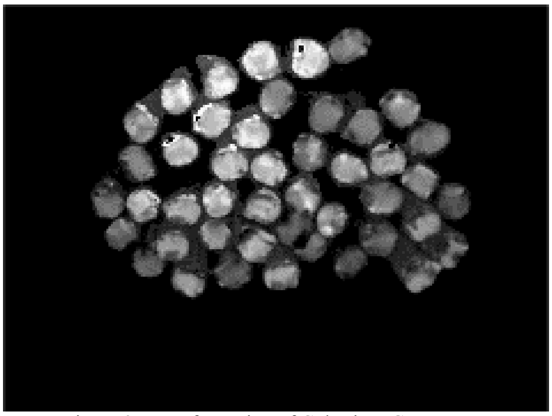

Figure 9. Transformation of Color into Gray Image

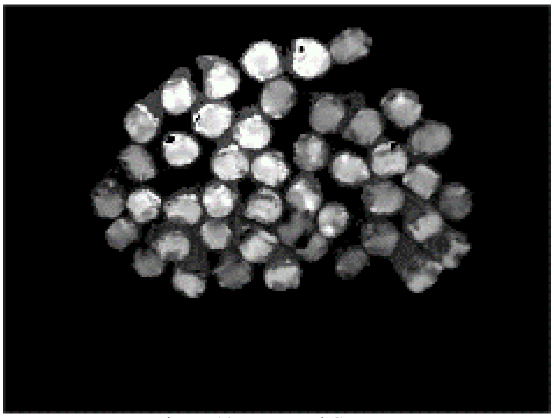

Figure 10. Increased Contrast

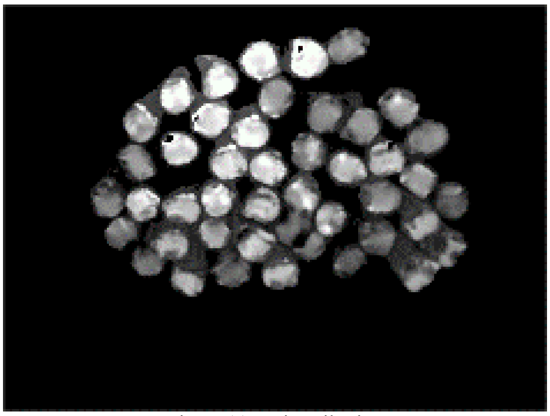

Figure 11. Noise Filtering

(a)

(b)

Figure 12. With and Without Overlapped Circles

Figure 13. Detecting Round Objects Using Hough Transform

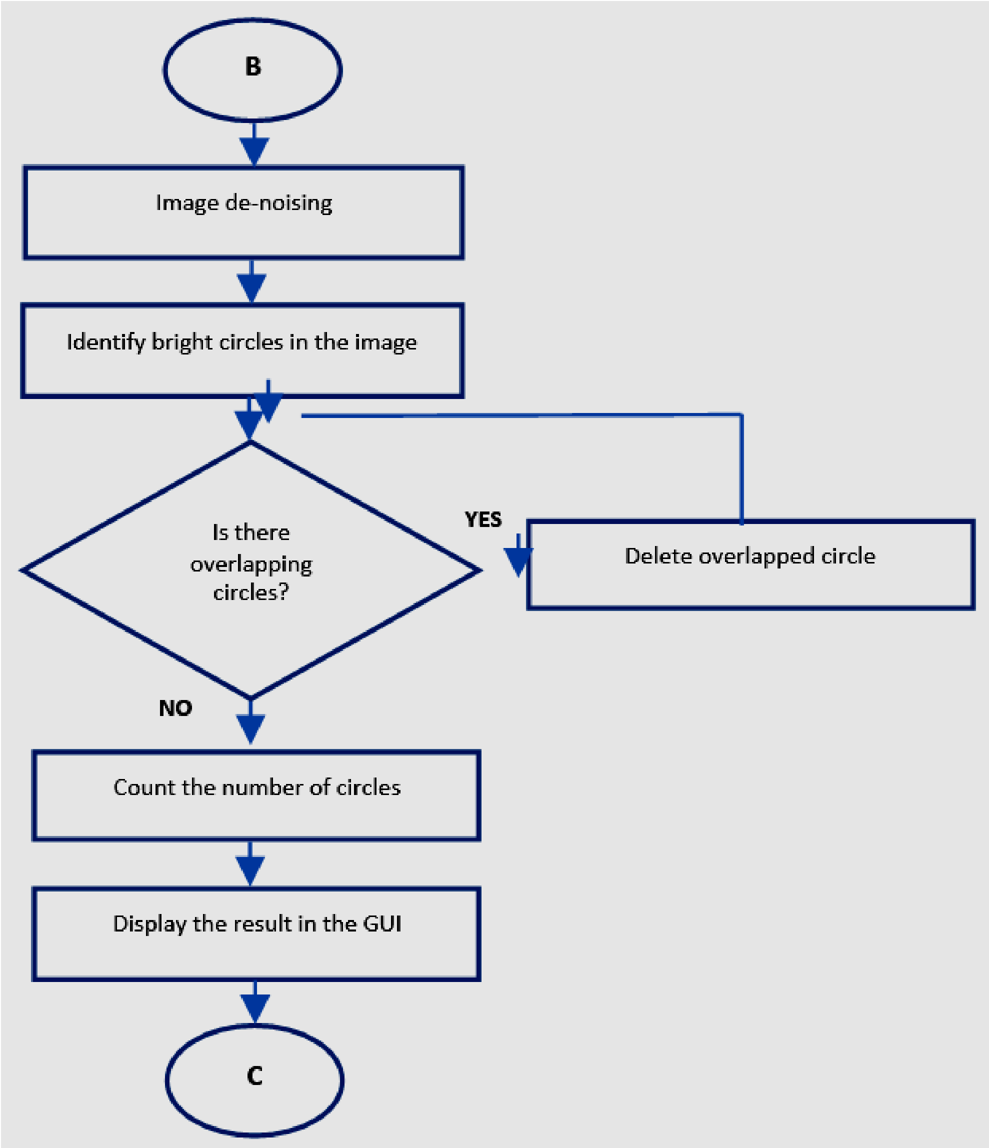

Figure 14. Image Processing Flow Chart B

B.3. Validation of the Result

The last section is the validation of the result. After counting the rebar, the system will compare the output quantity to the expected quantity shown in figure XVI. If the result is same, the output will be recorded on the table in GUI. If the result is not the same, the alarm will be triggered to alert the bundling personnel to remove the bundle rebar from the line. A thorough manual count will be done on the bundle in question to identify the cause of difference. After it is corrected, it will be again re-inputted to the system to check if it is correct. The flowchart is shown on figure 15.

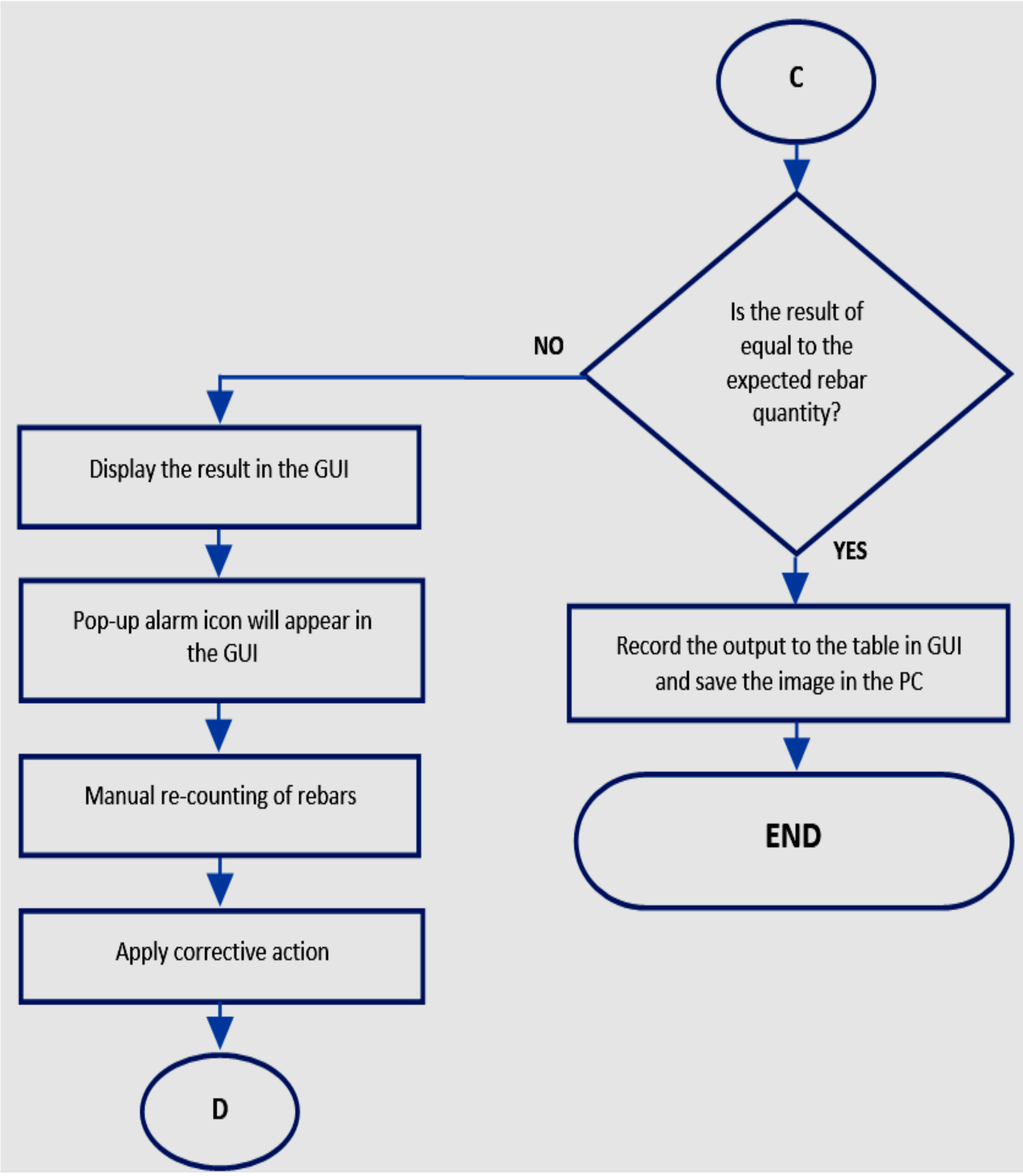

Figure 15. Validation of the Result's Flow Chart

Figure 16. GUI showing the output quantity of the system and the standard quantity

IV. RESULT AND DISCUSSION

The researchers performed actual tests for different rebar diameters and lengths to check its operational functionality in terms of counting rebars. The evaluation report is the basis to know how accurate and functional the behavior of the prototype is. It will also show if the entire component of the prototype works based on the stated objectives. The Chi-square goodness of fit test statistical method is used to evaluate the prototype's functionality whether it behaved and functioned accordingly as it was developed. The null hypothesis in this study is the output rebar quantity of the system is the same with the standard rebar quantity while the alternative hypothesis is the output rebar quantity of the system is not the same with the standard rebar quantity.

TABLE II. SUMMARY OF CHI-SQUARE GOODNESS OF FIT TEST

Number of sample, n	Degrees of Freedom (n-1)	Test Statistic x^2	Critical Test Statistic, cx^2	Significance Level, α	P-value	Remarks
41	40	0.0553	55.76	0.05	0.99	Non-rejection of HO

Table II shows that the values of test statistics is smaller than the critical test statistic values which leads to non-rejection of null hypothesis in all rebar sizes and commercial lengths. Also, the obtained P-value is 0.99 which greatly implied that the prototype is functioning based on the specification on how it has been designed and defined.

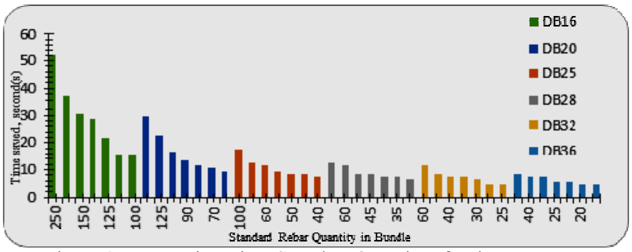

Figure 17. Increasing Time Saved as Quantity of Rebar Increases

Figure 17 shows that for different rebar diameters and commercial lengths, the time consumed in using the prototype to count rebar is faster than the manual counting method. It also shows that the saved time is more pronounced if there are more rebars in a bundle.

V. CONCLUSION

The study showed that the rebar counter was effective and more reliable than the manual counting method. The problem stated in this study which was the incorrect quantity of rebars in a bundle leaving the packaging line of steel bar rolling mill could be addressed. With the aid of the system, all bundled rebars leaving the packaging line could be checked and validated to help avoid one cause of miscount in quantity of rebars. The main objective of the study which is the avoidance of inexact number of rebars leaving the packaging line by developing image processing-based rebar counter that validates the correctness of the quantity is achieved. The results of the test conducted showed that the component of the system was functioning or functioned as a group based on the stated objectives to ultimately count the rebars in a bundle.

The chi-square goodness of fit test results showed the effectiveness of the system in counting rebars. The result was the acceptance of null hypothesis, the output rebar quantity of the system was the same with the standard rebar quantity, for different rebar diameter and commercial length. Aside from its effectiveness in counting rebar, the time saved using the prototype was enormous compared to the manual counting method. The critical test was 55.76 having 41 samples and 0.05 significance level. The obtained test statistic was 0.055, which was far smaller than the critical test statistic, with high probability value of 0.99.

Overall, it was proven that the rebar counter using image processing technology by means of k-means and Hough transform algorithm was one feasible way of counting rebar in steel bar rolling mill. The rebar counter checked the quantity of rebars in a bundle that left the packaging line. This would prevent the erroneous count of rebars in bundles that necessitated multiple rechecking and delayed in the warehousing and delivery areas.

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