Sri Lankan Currency Detector for Visually Impaired People

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Abstract*—Blind people face more difficulties in day to day life. One pressing problem is they also want to use physical currency (notes and coins) as others. They always have a hard time when trying to recognize the value of a currency, we intend to address this matter by developing a mobile application for blind people. We are going to implement this currency recognition mobile application along with counting and voice command compatibility and also this application is having user-friendly interfaces, therefore easy to negotiate. By using this mobile application blind people can give voice commands to navigate and the start intended to function as a currency recognition or counting as a pleased. We are going to use the user's mobile phone camera to get input into the app then classify the currency as a note or a coin. After that extract the features of the currency note and coin by using Convolutional Neural Network and predicting the value of the currency note and coin. This mobile application can extract the value of the coins and notes without any issue. Finally, we used Artificial Neural Network for the classification of notes and coins. Processing it and get the real value of the notes. Finally, train the Sinhala and English voice command using the CNN model and get them out as a voice.

Keywords—Convolutional Neural Network (CNN), Mel – frequency Cepstral Coefficient(MFCC)

I. Introduction

Visually impaired people face vast number of difficulties while carrying out their day today activities [1]. Among them dealing with currency is a major issue at hand since currency is the base of society. Visually impaired people could get cheated, scammed or even be a simple mistake either way it could harm their economy due to the fact that they have a difficult time identifying currency correctly. Purpose of this paper is to provide aid with identifying Sri Lankan currencies. With innovation of technology most countries have designed their own currencies [2]. But in Sri Lanka no such system available to aid visually impaired people. Nearly a one million out of the 21 million population of Sri Lanka suffer from visually impaired conditions, which is almost 5% of the total population of Sri Lanka. There are physical ways to identify notes implemented into notes that are purely indented to aid visually impaired people. But these solutions are not reliable as they should be. With usage of notes these signs could get worn out or in separable completely rendering those unreliable as a identifying method. With our "Sri Lankan Currency Detector for Visually impaired people" we are aiming to achieve Sri Lankan note recognition, Sri Lankan coin recognition and user friendly interaction methods to operate the app [2]. Currency recognition should be faster and accurate in order to be practically used in the society. System supposable should identify all the current valid currencies in Sri Lanka. System should contain update method allowing stake holders to keep the system updated

In design of system we have focused on three functionalities. Identifying notes, identifying coins and also new image training system are included in the design. Notes recognition sourly focused on Sri Lankan notes while coin recognition focused on Sri Lankan coins. Standalone image trainer is developed to aid admins with training new images into the system without accessing the backend of "Sri Lankan currency detector for visually impaired people"

II. RELATED WORK

The currency recognition system for blind people offers several main functions. Identifying notes, identifying coins, counting values, and offer in offline. Present days having some apps that offer the above-mentioned functions but either of the apps does not offer all the functions at once. For

instance, “MTC money reader” offers to identify notes and identifying coins. Moreover “Ideal Us currency identifier” offers the same capabilities while “Euro coin” offers only a coin identifying function. None of the apps does offer a voice recognition system for navigation through the app. “Sri Lankan Currency Detector for Visually impaired people” primarily focuses on Sri Lankan currency [3][4].

Table 1- Research Gap

Feature	MCT money reader	Ideal US currency identifier	Euro coin detector	Proposed system
Identified currency notes	√	√	×	√
Identified currency coins	√	√	√	√
Segmentation of images	×	×	×	√
Image processing training model	×	×	×	√
Free app	×	×	×	×

III. METHODOLOGY

Our research methodology is as shown below it contains brief and informatics descriptions and explanation of research findings, difficulties met while processing.

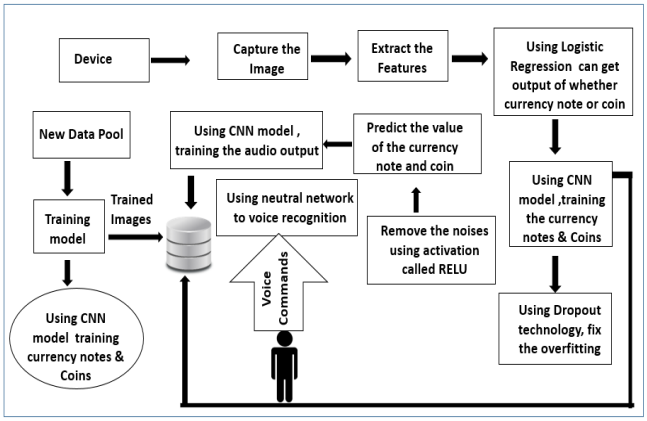

Figure 1: system overview diagram

Figure 1 is the basic overview of “Sri Lankan Currency Detector for Visually Impaired People” process begins with image capturing through device camera, then the image is begin processed for feature extraction. Next process is the feature extraction. With feature extraction CNN can use those features to recognize the notes and coins by comparing with existing database of trained data. This training model can be trained for higher efficiency with new data pool.

A. Convolutional Neural Network

There are many more feature extraction techniques like CNN, ORB algorithm, Scale-invariant feature transform algorithm (SIFT)algorithm, vector quantization, and histogram modeling, Laplacian of Gaussian strategy, Robert edge detection technique, and many more. In the world, there are inbuilt currency recognition systems with the use of the aforementioned techniques. The accuracy rate of every technique is varying from one to another. In most of the researches, implementers have used CNN technique to develop the feature extraction model. CNN technique gives a higher accuracy rate than the other techniques [5].

Because CNN is the best feature extraction technique we also used CNN as the main technique in our research. In there we implemented three main models using CNN. Those three functions are the specification of currency notes and coins, segmentation of currency notes and coins. The accuracy rate we got after training three models is very high.

In the segmentation of the currency note and coin function, we used five CNN layers. This function is predicting the currency is a note or a coin. If it is a note it is passing to the note detection model and extract the features otherwise if it is a coin it is passing to the coin detection model and extract the features.

Currency notes are having various features like color, size, images embedded in the notes. After detecting every feature only a mobile application is going to detect the value of the currency note. While implementing the CNN model for extraction of currency notes we used four

CNN layers to detect every feature. The first CNN layer of the currency recognition model is going to extract the very basic feature of the note like edges, color, gradient orientation of the input image. In ascending order next three CNN layers going to extract the architecture adapts and other advanced features in the currency note. Based on the features the final model is identifying the value of the currency note[6].

Currency coin recognition is more difficult than currency note detection. Most of the currency coins’ head side is having Sri Lankan emblem and most of the coins are similar in size. Therefore, coin detection is more difficult. Because of these reasons while implementing the coin recognition model we used five CNN layers to extract the features of the coin. Same to currency note feature extraction, the first CNN layer of the currency coin recognition model also going to extract very basic features like edge, color, gradient orientation of the input image. In the rest, CNN layers going to extract the architecture adapts and other advanced features in the currency coin. Based on the features final model is identifying the value of the currency coin [7].

“Detect Me” functions on CNN's that have previous data and training data of the system. These trained data play a vital part since these data are being used to compare with the image that has been taken from the device's camera. These data had been trained using the traditional way by feeding

manually into the network. But with this standalone app users can feed images directly into the CNN training these intended images without using a manual method. CNN is the utmost fastest method that can be utilized to train and extract features from an image. CNN can grow over time due to new additions that could feed through the standalone app.

B. Logistic Regression

In here currency image segmentation function, we used the basics of logistic regression function called ***sigmoid***, it is even used as an activation function of neural network layers for filtered specify features of currency image [8].

Sigmoid activation function:

$$\text{sigmoid}(x) = 1 / (1 + \exp(-x))$$

Applies the sigmoid activation function. For small values (<- 5), sigmoid returns a value close to (0) zero, and for large values (>5) the result of the function gets close to (1) One According to this function, we used one neuron to test. Hence the final result of the last hidden layer of the neuron is greater than
0.5, it is identified as a currency note. If not, it is also identified as a coin. Let 0.5 be the default value [9].

Sigmoid is equivalent to a 2 -element SoftMax where the second element is assumed to be zero. The sigmoid function always returns a value between 0-1.

C. Overfitting

In our research domain, we used thousands of currency note and coin images to train for getting accurate results but somehow in cases those images also not enough to gain the results because every neuron is used to share the same heavy details of currency notes and coins as a result of that over-fitting may occur. To mitigate this problem Dropout function is used [10].

D. Data Collection

We needed different types of datasets to perform this task before implementing the system. First, we had to take a large number of coins and notes for the identification process. Coins currently used in Sri Lanka are Rs. 1, Rs. 2, Rs. 5, and Rs. 10 as well as Rs. 20, Rs. 50, Rs. 100, Rs. 500, Rs. 1000 and Rs. 5000. There are different versions of all these notes and coins. Due to the COVID 19 situation prevailing in the country, we have not been able to obtain data from the bank. Therefore, we prepared our database with the help of friends. For all these coins and notes, we received nearly 50,000 pictures. Further, both sides of the coins and notes were captured for data training.

For training, the voice recognition model has to be done with word by word, and words have to be dismantled into smaller sub-functions. This requires hours and hours of voice cuts for a single word. This makes up for thousands and thousands of voice cuts. Slice its harder to find Sinhala language voice cut data bulks. We had to do it ourselves and find people that willing to do hundreds of voice recordings for one word. Then we used a data duplicated method to multiply the voice recordings we have. This allows us to increase the accuracy of the recognition. Since we are lacking data variety accuracy towards accents is lacking. Below figure 2 is showcasing the sample dataset we utilized in the training process.

Figure 2: Sample Data set

E. Python.

Using a python flak user-friendly image processing model will be implemented. With this, we have made sure app owners can add new currency notes/coins into the app database without using any programming knowledge [11][12]. Users have to add a sufficient amount of images and begin training. If a successful new image will be added to the app or users will have to keep training until the algorithm makes the progress.[12][13].

F. React Native

When implementing the app react native environment is used. React allows designing an app that functions on both android and IOS platforms[14]. Respective react related third-party libraries will be used in the process[15][16]

IV. RESULTS

After training the system decent enough we were able to extract the positive result from the system.

G. Results of Segmentation

Under classification, we were able to reach an accuracy of 0.5485 with a relatively small data set that only contain around 50, 000 images. We were able to utilize all the parameters in training resulting in good accuracy. The below figure 3 is a screenshot from the results we extracted.

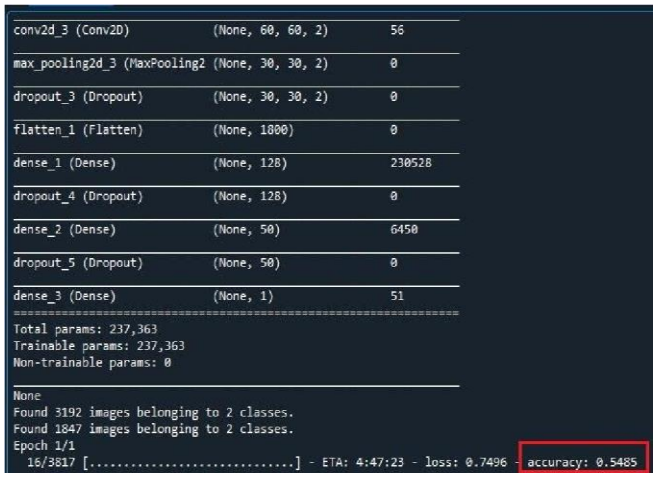

Figure 3: Accuracy rate of segmentation

If note detection we were able to reach a bit higher accuracy than the classification even though the dataset is smaller than classification.

H. Results of Note Detection

Note detection recognizes the notes with 0.6667 accuracies. We were able to utilize all the parameters here also as trainable parameters. Dataset roughly contains 50,000 images. The below figure 4 is a screenshot of the result that we achieved.

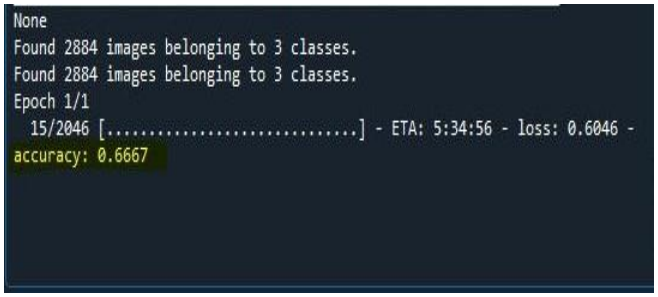

Figure 4: Accuracy rate of note detection

I.Result of Coin Detection

We achieved 0.6970 accuracy where coin detection is, with a lesser loss count of 0.5888. in coin, detection accuracy is helped with having lesser classes to identify than other functions 0.6970 accuracies are achieved from a smaller dataset that only contained 50,000 images. The below figure 5 is a screenshot of the result.

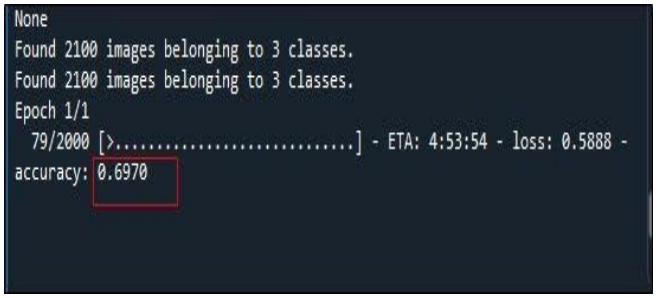

Figure 5 Accuracy rate of coin detection

We were able to achieve higher accuracy on notes due to their physical size and unique features over coins where features are less and therefore recognition accuracy is lesser. But with a bit larger dataset we were able to obtain with detecting my research. They showcase the various coins and notes detected by the app respectively. For demonstration and paper circumstances we have to utilize screen alert in addition to the voice outputs. Below figure 7 and figure 8 is showcasing the note recognition results and coin recognition respectively.

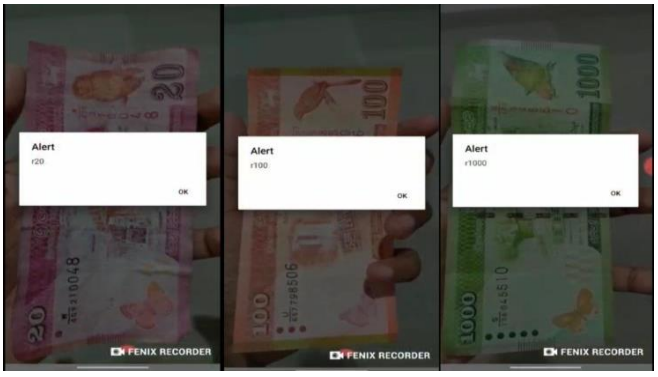

Figure 6: Final output of recognized currency notes

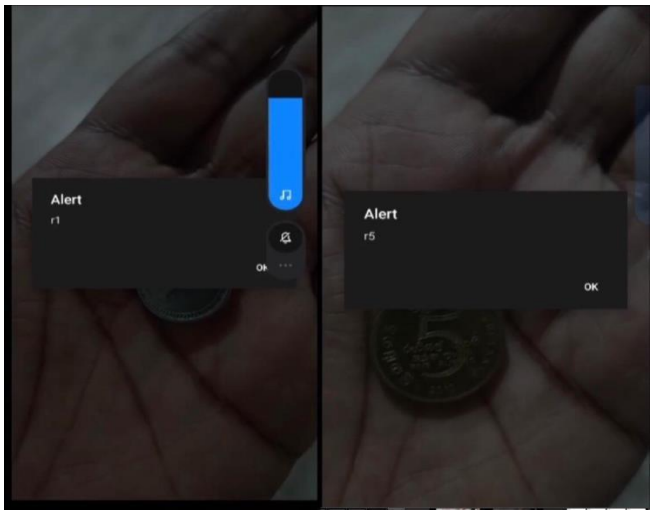

Figure 6: Final output of recognized currency coins

Figure 9 and other is related to the standalone app design for training newer images for the "Detect Me" app. The following shows the final output of the standalone trainer application. It will indicate that it has added a trainable image to the system and it's ready to start training on command.

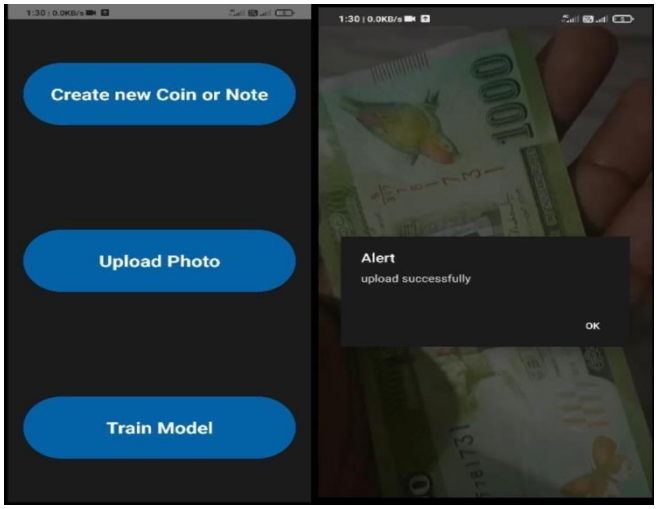

Figure 7; The interface of image trainer model and sample output

V. CONCLUSION

As an overall conclusion we are confident that research on "Sri Lankan Currency Detector for Visually impaired people" is holding higher significance due to the fact that it could potentially aid 5%of country's population in their deficiency of currency recognition. These types of apps could aid visually impaired and non disable people in various occasions. Providing higher accuracy user can rely on the system without having doubts. Being able to deploy freely app could be highly popular and help full of the targeted audience.

Note recognition and coin recognition is achieved through CNN network rendering it reliable and faster solution. This CNN helps to minimize the time for recognition and maize the load on device, this allows app to operate on various mobile devices without consuming higher amount of resources. This "Sri Lankan Currency detector for visually

impaired people" is highly reliable, faster and highly compatible solution for the problem at hand.

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REFERENCES

[1] M. Sarfraz, "An Intelligent Paper Currency Recognition System," *Procedia Comput. Sci.*, vol. 65, no. Iccmit, pp. 538–545, 2015, doi: 10.1016/j.procs.2015.09.128.

[2] D. Nagajyothi and P. Siddaiah, "Speech recognition using convolutional neural networks," *Int. J. Eng. Technol.*, vol. 7, no. 4.6 Special Issue 6, pp. 133–137, 2018, doi: 10.14419/ijet.v7i4.6.20449.

[3] . K. C., "Recent Developments in Paper Currency Recognition System," *Int. J. Res. Eng. Technol.*, vol. 02, no. 11, pp. 222–226, 2013, doi: 10.15623/ijret.2013.0211034.

[4] J. Mehta, "ences Refer," vol. 115, no. 20, pp. 8–10, 2015.

[5] V. Abburu, S. Gupta, S. R. Rimitha, M. Mulimani, and S. G. Koolagudi, "Currency recognition system using image processing," *2017 10th Int. Conf. Contemp. Comput. IC3 2017*, vol. 2018-Janua, no. August, pp. 1–6, 2018, doi: 10.1109/IC3.2017.8284300.

[6] X. Lu, X. Duan, X. Mao, Y. Li, and X. Zhang, "Feature Extraction and Fusion Using Deep Convolutional Neural Networks for Face Detection," *Math. Probl. Eng.*, vol. 2017, 2017, doi: 10.1155/2017/1376726.

[7] O. Abdel-Hamid, A. R. Mohamed, H. Jiang, L. Deng, G. Penn, and D. Yu, "Convolutional neural networks for speech recognition," *IEEE Trans. Audio, Speech Lang. Process.*, vol. 22, no. 10, pp. 1533–1545, 2014, doi: 10.1109/TASLP.2014.2339736.

[8] S. Sperandei, "Understanding logistic regression analysis," *Biochem. Medica*, vol. 24, no. 1, pp. 12–18, 2014, doi: 10.11613/BM.2014.003.

[9] E. Signal and P. Conference, "IMAGE SEGMENTATION USING SPARSE LOGISTIC REGRESSION WITH SPATIAL PRIOR Pekka Ruusuvuori , Tapio Manninen , Heikki Huttunen Department of Signal Processing , Tampere University of Technology , Tampere , Finland," no. Eusipco, pp. 2253–2257, 2012.

[10] P. R. Cohen and D. Jensen, "Over tting Explained," no. April 2000, 2013, [Online]. Available: https://www.researchgate.net/publication/2475394_Overfitting_Explained.

[11] F. A. Aslam, H. N. Mohammed, J. M. M. Munir, and M. A. Gulamgaus, "Efficient Way Of Web Development Using Python And Flask," *Int. J. Adv. Res. Comput. Sci.*, vol. 6, no. 2, pp. 54–57, 2015, [Online]. Available: www.ijarcs.info.

[12] X. Cai, H. P. Langtangen, and H. Moe, "On the performance of the Python programming language for serial and parallel scientific computations," *Sci. Program.*, vol. 13, no. 1, pp. 31–56, 2005, doi: 10.1155/2005/619804.

[13] D. A. Hossain and M. A. Rafsan, "Bridging Advanced Data Science, Machine Learning and Future of Accounting and Auditing: A Theoretical Review," *SSRN Electron. J.*, pp. 1–8, 2020, doi: 10.2139/SSRN.3667735.

[14] W. Danielsson, "React Native Application Development," *Linköpings Univ.*, p. 70, 2016, doi: diva2:998793.

[15] A. Beshir, "Writing Cross-Platform Development with React Native," 2016, [Online]. Available: https://www.infoq.com/articles/react-native-introduction.

[16] G. Amaral *et al.*, "No 主観的健康感を中心とした在宅高齢者における 健康関連指標に関する共分散構造分析Title," *J. Petrol.*, vol. 369, no. 1, pp. 1689–1699,2013,doi: 10.1017/CBO9781107415324.004