

Recognition of Baybayin (Ancient Philippine Character) Handwritten Letters Using VGG16 Deep Convolutional Neural Network Model

Lyndon R. Bague¹, Romeo Jr. L. Jorda², Benedicto N. Fortaleza³, Andrea DM. Evanculla⁴, Mark Angelo V. Paez⁵, Jessica S. Velasco⁶

¹Department of Electrical Engineering, Technological University of the Philippines, Manila, Philippines

^{2,4,5,6}Department of Electronics Engineering, Technological University of the Philippines, Manila, Philippines

³Department of Mechanical Engineering, Technological University of the Philippines, Manila, Philippines

^{1,2,3,4,5,6}Center for Engineering Design, Fabrication, and Innovation, College of Engineering, Technological University of the Philippines, Manila, Philippines

ABSTRACT

We proposed a system that can convert 45 handwritten baybayin Philippine character/s into their corresponding Tagalog word/s equivalent through convolutional neural network (CNN) using Keras. The implemented architecture utilizes smaller, more compact type of VGG16 network. The classification used 1500 images from each 45 baybayin characters. The pixel values resulting from the resized characters (50x50 pixels) of the segmentation stage have been utilized for training the system, thus, achieving a 99.54% accuracy. To test the developed recognition system, 90 handwritten baybayin characters were captured in real time using its 1080P Full-HD web camera. Next, the system will classify the test sample. Lastly, the corresponding Tagalog word output is shown on the screen for the user. The overall accuracy for the testing phase is 98.84%. As a result, the proposed system will find possible applications in character extraction in documents and any related translation of handwritten document to structural text form.

Key words : Baybayin, character recognition, computer vision, convolutional neural network, deep learning

1. INTRODUCTION

Baybayin, comes from the word “baybay” which means “to spell” in Tagalog, was used in the Philippines as a writing system prior to Spanish colonial period to the early eighteenth century [1],[2]. It is an abugida whose units of the writing system are composed of a consonant letter followed by a vowel notation. It resembles other Indic scripts, e.g., Devanagari, Javanese and Tamil. In 2018, the Philippine House Bill 1022 or more commonly known as the “National Writing System Act” which declares Baybayin as the official national writing system was proposed which aims to promote and revive the use of baybayin. This led our team to study about the character recognition and make use of the current effective model to implement in the baybayin character recognition. The focus

of this proposed study is to translate baybayin characters (based on the original 1593 Doctrina Christiana) into its corresponding Tagalog word equivalent.

The proposed software employed Deep Convolutional Neural Network (DCNN) model with VGG16 as the architecture and image processing module using OpenCV library to perform character recognition. There are two (2) ways to input data into the system, real – time translation by using web camera or by uploading image file into the system. The model was trained using the data acquired that reached up to 2400 per character multiplied by 17 characters, 3 for vowels (A, E/I, O/U) and 14 for consonants (Ba, Ka, Da/Ra, Ga, Ha, La, Ma, Na, Nga, Pa, Sa, Ta, Wa, Ya), with a total number of images contained in the dataset of 108,000.

Similar studies on character recognition e.g., Javanese and Devanagari (which resembles to the Baybayin characters), were conducted using deep learning. [3] developed a handwritten Javanese character recognition system which uses convolutional neural network and deep neural network having accuracies of 70.22% and 64.65%, respectively. Meanwhile, [4] proposed a handwritten Devanagari character classification tool which is implemented using CNN achieving a 94.49% validation accuracy and 95.46% test accuracy. Meanwhile, [5] developed an automated reader for baybayin scripts which used Berthod and Maroy’s Primitive method and Freeman Chain Coding which are employed by means of OpenCV.

Widiarti and Wastu [6] utilized Hidden Markov Model (HMM) to categorize the extracted vertical and horizontal features of Javanese characters. Shubhangi and Hiremath [7] used multiclass support vector machine (SVM) and micro features. The skeleton serves as the feature for extracting handwritten alphabets and numbers that were produced using a vector skeletonization algorithm. Hanmandlu and Murthy [8],[9] developed a Fuzzy model-based recognition of handwritten Hindi numerals and characters and 92.67% and 90.65% accuracies for Handwritten Devnagari numerals and

characters, respectively, were obtained. Some research uses different neural network to classify handwritten character. Attigeri [10] employs feed forward back propagation neural network in their system. Basu et al. [11] used MLP based pattern classifier for recognition of handwritten Bangla digits with a feature set of 76 features. Several other studies [12]-[13] show that were able to achieve image classification job with good outcome if they are joined with other suitable feature extraction methods. Meanwhile, deep learning and optical character recognition (OCR) was applied by [14] in Handwritten Phoenician Character Recognition. Neural network and OCR was used for Arabic handwriting recognition in [15]. Lastly, Tesseract OCR, Open CV, and deep learning algorithms were implemented by [16] in translation of text in images.

2. CHARACTER RECOGNITION USING TRANSFER LEARNING

Figure 1 shows the block diagram for the training and testing of baybayin character images. The dataset used in training the network was composed of images of handwritten baybayin characters from different people. Different strokes of baybayin writings per character were taken into consideration. The model is composed of 45 classes respectively named after baybayin characters (A BA KA DA GA LA etc.). Each class contains 1500 images. We used Digital Interface-IRIScan Anywhere 3 scanner to acquire images of the characters. After being scanned, images were automatically cropped. Open CV and Python was used in contouring of the scanned images then the images were cropped based on their text fields. The images will then be sorted and saved to their corresponding folders for the training.

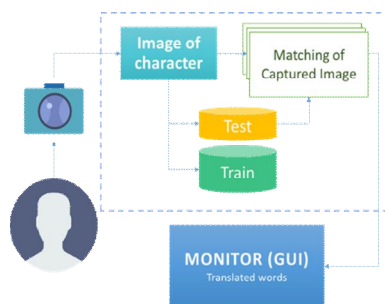


Figure 1: Block Diagram

Figure 2 shows the samples of the datasets gathered which were already cropped. To construct a network that can

properly classify the image to its corresponding character using a convolutional neural network, we used Keras and a Convolutional Neural Network architecture (VGG16) [17],[18] containing group of unlike layers for handling out of training of data.

We have partially divided our dataset in 80 by 20; 80% of the data was used for training and 20% for testing. This was made to evaluate the outcome of the utilized algorithm. The network was employed and trained through Keras and Tensorflow utilizing a Graphics Processing Unit GT-1030 GPU. Adam as its optimizer was used as a network. It used to train the network with a learning rate of 1e-3. For the network to be trained, 50 number of epochs were utilized with a batch size of 32. We resized the images to (50, 50,1) to perform the training and testing.

3. EXPERIMENTAL RESULTS

90 baybayin characters which were handwritten on a sheet of paper from 90 different people were captured in real time using a 1080P Full-HD web camera of the proposed baybayin character recognition system. To have better recognition, when writing more than one character, distance from each other must at least 0.5 cm apart and the paper with written character/s must be horizontally aligned. When the camera has already captured the handwritten character, the system will classify the test sample and compared it in the deposited characters in the database. Lastly, the equivalent Tagalog word output is shown on the screen as displayed in Figure 3. Figure 4 shows the confusion matrix of the developed baybayin character recognition system. Table 1 shows the accuracy rate and mean recognition time of every character from all the trials.

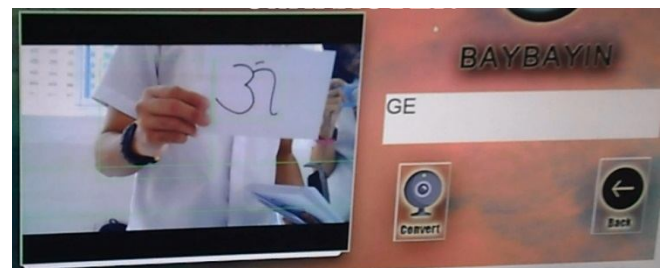


Figure 3: Actual testing of the baybayin character recognition system

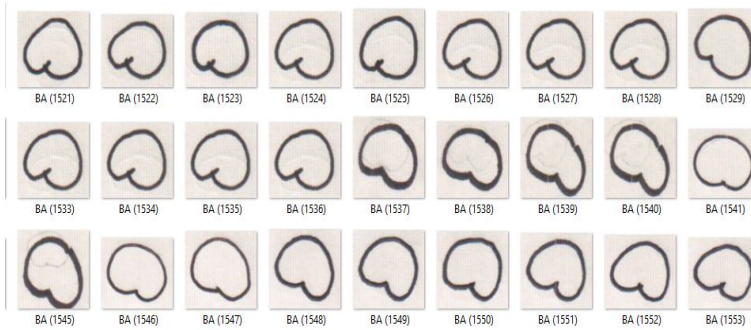


Figure 2: Sample data set of Baybayin character

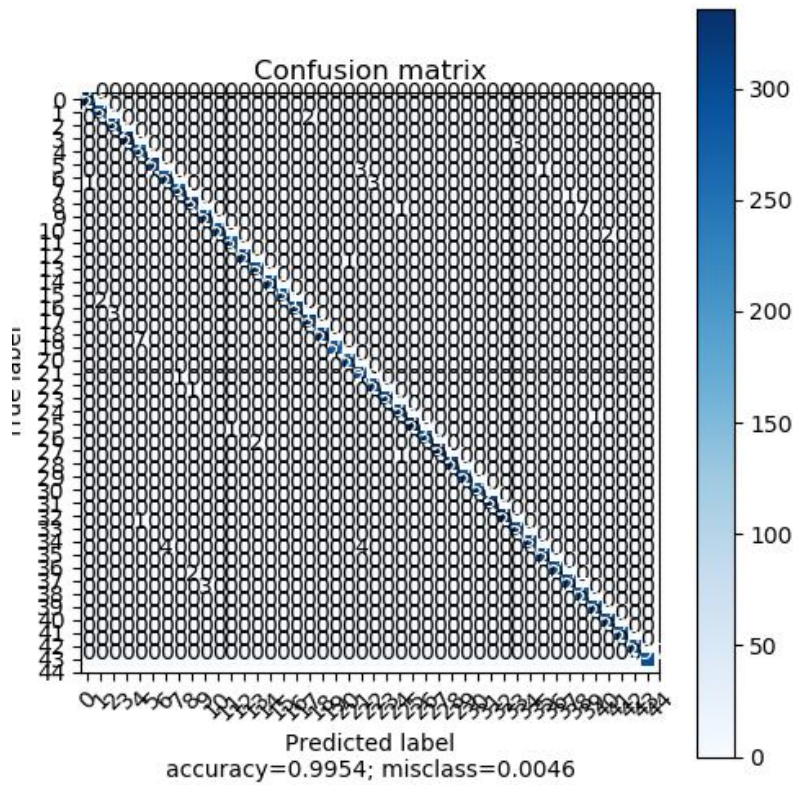


Figure 4: Confusion matrix of the Baybayin Character Recognition System

Table 1: Character Recognition Accuracy and Average Time

Character	Data Gathered		Character	Data Gathered	
	Accuracy (%)	Ave. Time (s)		Accuracy (%)	Ave. Time (s)
A	98.89	1.65	NE/NI	98.89	2.07
BA	100	1.6	NGE/NGI	100	1.98
KA	100	1.79	PE/PI	100	1.71
DA/RA	96.67	2.37	SE/SI	98.89	1.7

GA	98.89	1.88	TE/TI	98.89	1.82
HA	94.44	2.61	WE/WI	98.89	1.84
LA	96.67	2.21	YE/YI	98.89	2.02
MA	98.89	1.9	O/U	100	1.54
NA	97.78	2.2	BO/BU	98.89	1.73
NGA	98.89	2.32	KO/KU	100	1.88
PA	98.89	2.08	DO(U)/RO(U)	100	2.13

SA	98.89	2.27	GO/ GU	100	1.93
TA	96.67	2.26	HO/ HU	100	1.84
WA	95.56	2.45	LO/ LU	100	1.87
YA	97.78	2.06	MO/ MU	100	1.8
E/I	98.89	1.71	NO/ NU	97.78	2.2
BE/ BI	100	1.83	NGO/ NGU	100	1.9
KE/ KI	100	1.86	PO/ PU	94.44	2.66
DE(I)/ RE(I)	98.89	2.15	SO/ SU	100	1.82
GE/ GI	100	1.83	TO/ TU	100	1.66
HE/ HI	98.89	1.73	WO/ WU	98.89	1.71
LE/ LI	98.89	1.69	YO/ YU	98.89	1.91
ME/ MI	100	1.68	Overall Rating	98.84	1.95

4. CONCLUSION

The system was able to recognize the 45 baybayin characters registered in the system through real time recognition using camera. In the training and testing phase of the development of the project using deep learning, an accuracy of 99.54% and 98.84%, respectively, was obtained using real-time evaluation.

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REFERENCES

1. P. Morrow, **Baybayin, The Ancient Script of the Philippines**. 2002.
2. J. P. G. Potet, **Baybayin, the Syllabic Alphabet of the Tagalogs**. Lulu. com, 2018.
3. R. Khadijah and A. Nurhadiyah, **“Deep learning for handwritten Javanese character recognition,”** in *2017 1st International Conference on Informatics and Computational Sciences (ICICoS)*, 2017, pp. 59-64.
4. P. K. Sonawane and S. Shelke, **“Handwritten Devanagari Character Classification using Deep Learning,”** in *2018 International Conference on Information, Communication, Engineering and Technology (ICICET)*, 2018, pp. 1-4.
5. R. N. C. Recario, V. Y. Mariano, D. A. S. Galvez, and C. M. S. Lajara, **“An Automated Reader Philippine Baybayin Scripting Image Processing Methods,”** in *ICCC International Digital Design Invitation Exhibition*, 2011, pp. 75-76.
6. A. R. Widiarti and P. N. Wastu, **“Javanese character recognition using hidden Markov model.”** *International Journal of Computer, Electrical, Automation, Control and Information Engineering*, vol. 3, no. 9, pp. 2201–2204, 2009.
7. D. C. Shubhangi and P. S. Hiremath, **“Handwritten English Character and Digit Recognition Using Multiclass SVM Classifier And Using Structural Micro Features,”** *International Journal of Recent Trends in Engineering*, vol. 2, no. 2, pp. 2–4, 2009.
8. M. Hanmandlu, O. V. R. Murthy, and V. K. Madasu, **“Fuzzy Model based recognition of handwritten Hindi characters,”** in *9th Biennial Conference of the Australian Pattern Recognition Society on Digital Image Computing Techniques and Applications (DICTA 2007)*, 2007, pp. 454-461.
9. M. Hanmandlu, A. V. Nath, A. C. Mishra, and V. K. Madasu, **“Fuzzy Model Based Recognition of Handwritten Hindi Numerals using Bacterial Foraging,”** in *6th IEEE/ACIS International Conference on Computer and Information Science (ICIS 2007)*, 2007, pp. 309-314.
10. S. Attigeri, **“Neural Network based Handwritten Character Recognition system,”** *International Journal of Engineering and Computer Science*, vol. 7, no. 3, pp. 23761–23768, 2018.
11. S. Basu, N. Das, R. Sarkar, and M. Nasipuri, **“An MLP based Approach for Recognition of Handwritten ‘Bangla’ Numerals,”** *arXiv preprint arXiv:1203.0876*, 2012.
12. Y. H. Tay, P. Lallican, M. Khalid, C. Viard-gaudin, and S. Knerr, **“An Offline Cursive Handwritten Word Recognition System.”** in *Proceedings of IEEE Region 10 International Conference on Electrical and Electronic Technology. TENCON 2001 (Cat. No. 01CH37239)*, 2001, pp. 519-524.
13. S. Arora, D. Bhattacharjee, M. Nasipuri, D. K. Basu, and M. Kundu, **“Combining multiple feature extraction techniques for handwritten Devnagari character recognition,”** in *2008 IEEE Region 10 and the Third international Conference on Industrial and Information Systems*, 2008, pp. 1-6.
14. L. Sadouk, T. Gadi, E. H. Essoufi, and A. Bassir, **“Handwritten phoenician character recognition and its use to improve recognition of handwritten alphabets with lack of annotated data,”** *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 9, no. 1, pp. 171-181, 2020, doi: 10.30534/ijatcse/2020/26912020.

15. A. V. Zadgaonkar and R. S. Vairagade, “**An approach for translation of text in images using deep learning techniques,**” *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 9, no. 1, pp. 808-812, 2020, doi: 10.30534/ijatcse/2020/116912020.
16. M. Abdullah, A. Agal, M. Alharthi, and M. Alrashidi, “**Arabic handwriting recognition model based on neural network approach,**” *Int. J. Adv. Trends Comput. Sci. Eng.*, 2019. doi: 10.30534/ijatcse/2019/4581.120419.
17. B. Anilkumar and P. Rajesh Kumar, “**Tumor classification using block wise fine tuning and transfer learning of deep neural network and KNN classifier on MR brain images,**” *Int. J. Emerg. Trends Eng. Res.*, vol. 8, no. 2, 2020, pp. 574-583, 2020. doi: 10.30534/ijeter/2020/48822020.
18. L. K. S. Tolentino, R. O. Serfa Juan, A. C. Thio-ac, M. A. B. Pamahoy, J. R. R. Forteza, and X. J. O. Garcia, “**Static Sign Language Recognition Using Deep Learning,**” *International Journal of Machine Learning and Computing*, vol. 9, no. 6, 2019. doi: 10.18178/ijmlc.2019.9.6.879
19. J. Velasco, J. R. Ang, J. Caibigan, F. M. Naval, N. Arago, and B. Fortaleza, “**Identification of Normal and Diseased Lungs using X-ray Images through Transfer Learning,**” *International Journal of Advanced Trends in Computer Science and Engineering*, vol. 9, no. 4, 2020. doi: 10.30534/ijatcse/2020/301942020