# THRESHOLD CENTER-SYMMETRIC LOCAL BINARY CONVOLUTIONAL NEURAL NETWORKS FOR BILINGUAL HANDWRITTEN DIGIT RECOGNITION

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A thesis submitted in
fulfillment of the requirement for the award of the
Doctor Of Philosophy in Information Technology

Faculty of Computer Science and Information Technology
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MARCH 2022

# DEDICATION

I would like to dedicate my thesis to my loving parents for their sacrifices and love,

to my wife for her continuous prayers and encouragement,

to my brothers and sisters for their support throughout my graduate studies,

to my sons and daughter who made my life happier and more pleasant,

to all my extended family members, my friends, and all those who helped me to complete my studies,

to my professors who instilled in me the love of knowledge.

## ACKNOWLEDGEMENT

In the name of Allah, the Most Gracious and Most Merciful, I would like to thank Allah Subhana Wa Ta'ala for helping me compile and complete this thesis.

I would like to express my most sincere gratitude and appreciation to my supervisor, Professor Dr. Rozaida Binti Ghazali, for her constant support throughout my studies. I cannot express enough thanks to my supervisor for her continued support and encouragement, Professor Dr. Rozaida Binti Ghazali. I offer my sincere appreciation for the learning opportunities provided by my supervisor. I am fortunate to have her as my supervisor, and I will always be grateful for her guidance and encouragement. My appreciation goes to Universiti Tun Hussein Onn Malaysia, which provided me with a pleasant working environment and many resources. I would also like to thank Hodeidah University for its support and for giving me this opportunity to complete my Ph.D. degree.

My parents' spiritual support, care, unconditional love, and prayers have enabled me to complete my journey so far. I cannot thank them enough for what they did to me throughout my life. In addition, I owe special thanks to my brothers and sisters for their support, encouragement, and sincere prayers. Furthermore, my completion of this research could not have been accomplished without my friends' support of my friends, Waddah and Nayef. To Mohammed, Sama, and Laith, my children, – thank you for allowing me time away from you to research and write.

Finally, to my caring, loving, and supportive wife, Rania Al-Asbahy: my deepest gratitude. Your encouragement when the times got rough is much appreciated and duly noted. It was a great comfort and relief to know that you were willing to provide management of our household activities while I completed my work. My heartfelt thanks.

# ABSTRACT

Arabic and English handwritten digit recognition is a challenging problem because the writing style differs from one writer to another. In middle east countries, many official forms are prepared to be written using either Arabic or English languages. However, some people fill the form using both languages (Arabic and English), which adds more challenges to recognize digits. Nowadays, deep learning approaches are considered the hot trend of new research, including Convolutional Neural Networks (CNN). CNN is used in many applications and modified to produce other models such as Local Binary Convolutional Neural Networks (LBCNN). LBCNN was created by fusing Local Binary Pattern (LBP) with CNN by reformulating LBP as a convolution layer called Local Binary Convolution (LBC). However, LBCNN suffers from the random assign 1, 0, or -1 to LBC weights, making LBCNN less robust. Nevertheless, using another LBP-based technique such as Center-Symmetric Local Binary Patterns (CS-LBP) can address such issues. In this thesis, a new model based on CS-LBP is proposed called Center-Symmetric Local Binary Convolutional Neural Networks (CS-LBCNN) that addresses the issues of LBCNN. Further, an enhanced version of CS-LBCNN is proposed called Threshold Center-Symmetric Local Binary Convolutional Neural Networks (TCS-LBCNN) that addresses another issue related to the zero-thresholding function. The proposed models are compared against state-of-the-art techniques that used the MNIST and MADBase as a bilingual dataset. The proposed TCS-LBCNN model proves its ability to give a more accurate and significant classification rate than the existing LBCNN models. For the bilingual dataset, the TCS-LBCNN enhances the performance of LBCNN and CS-LBCNN, in terms of accuracy, by 0.15% and 0.03%, respectively. In addition, the comparison shows that the accuracy acquired by TCS-LBCNN is the second-highest using the MNIST and MADBase datasets.

# ABSTRAK

Pengecaman digit tulisan tangan Arab dan Inggeris merupakan masalah yang mencabar kerana gaya penulisan berbeza antara penulis. Di negara timur tengah, banyak borang rasmi disediakan untuk ditulis sama ada menggunakan bahasa Arab atau Inggeris. Walau bagaimanapun, sesetengah orang mengisi borang menggunakan kedua-dua bahasa menyebabkan lebih banyak cabaran untuk mengenali digit. Kini, pendekatan pembelajaran mendalam dianggap sebagai corak terkini di dalam penyelidikan, termasuk *Convolutional Neural Networks* (CNN). CNN digunakan dalam banyak aplikasi dan diubahsuai menghasilkan model baru seperti Local *Binary Convolutional Neural Networks* (LBCNN). LBCNN dicipta dengan menyatukan *Local Binary Pattern* (LBP) bersama CNN dan merumuskan semula LBP sebagai lapisan konvolusi yang disebut *Local Binary Convolution* (LBC). Namun begitu, LBCNN mengalami kelemahan penetapan rawak 1, 0, atau -1 ke pemberat LBC, menjadikan LBCNN kurang mantap. Walau bagaimana pun, menggunakan teknik LBP lain seperti *Center-Symmetric Local Binary Patterns* (CS-LBP) dapat mengatasi masalah tersebut. Di dalam tesis ini, model baru CS-LBP telah dicadangkan, yang dinamakan *Center-Symmetric Local Binary Convolutional Neural Networks* (CS-LBCNN) yang dapat menangani isu-isu pada LBCNN. Selanjutnya, versi tambahbaik CS-LBCNN dicadangkan, iaitu *Threshold Center-Symmetric Local Binary Convolutional Neural Networks* (TCS-LBCNN) yang menangani masalah fungsi *zero-thresholding*. Model yang dicadangkan dibandingkan dengan teknik terkini menggunakan MNIST dan MADBase sebagai set data dwi-bahasa. TCS-LBCNN yang dicadangkan membuktikan keupayaannya untuk memberikan kadar klasifikasi yang lebih tepat dan ketara daripada model LBCNN yang sedia ada. Untuk set data dwi-bahasa, TCS-LBCNN meningkatkan prestasi LBCNN dan CS-LBCNN, dari segi ketepatan, masing-masing sebanyak 0.15% dan 0.03%. Di samping itu, perbandingan menunjukkan bahawa ketepatan yang diperoleh oleh TCS-LBCNN adalah yang kedua tertinggi menggunakan set data MNIST dan MADBase.

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## LIST OF SYMBOLS AND ABBREVIATIONS

| | |
|---|---|
| AUC | - Area Under ROC Curve |
| ANN | - Artificial Neural Networks |
| CS-LMP | - Center Symmetric Local Multilevel Pattern |
| CS-LTP | - Center Symmetric Local Ternary Patterns |
| CS-LBC | - Center-Symmetric Local Binary Convolution |
| CS-LBCNN | - Center-Symmetric Local Binary Convolutional Neural Networks |
| CS-LBP | - Center-Symmetric Local Binary Patterns |
| CI | - Confidence Interval |
| CNN | - Convolutional Neural Networks |
| DCNN | - Deep Convolutional Neural Networks |
| DL | - Deep Learning |
| DNN | - Deep Neural Network |
| ResNet | - Deep Residual Network |
| DCT | - Desecrates Cosine Transform |
| EDH | - Edge Direction Histogram |
| k-NN | - k-Nearest Neighbour |
| LR1 | - Learning Rate Approach 1 |
| LR2 | - Learning Rate Approach 2 |
| LBC | - Local Binary Convolution |
| LBCNN | - Local Binary Convolutional Neural Networks |
| LBGC | - Local Binary Gradient Contours |
| LBP | - Local Binary Pattern |
| LCvMSP | - Local Concave and Convex Microstructure Patterns |
| LDTP | - Local Directional Ternary Pattern |
| LSTM | - Long Short-Term Memory |
| MAD | - Median Absolute Deviation |
| MLP | - Multilayer Perceptron |

| | |
|---|---|
| MSPN | - Multi-stage Spatially-sensitive Pooling Network |
| NN | - Neural Networks |
| OCR | - Optical Character Recognition |
| ROC | - Receiver Operating Characteristics |
| ReLU | - Rectified Linear Unit |
| SVM | - Support Vector Machine |
| TCS-LBC | - Threshold Center-Symmetric Local Binary Convolution |
| TCS-LBCNN | - Threshold Center-Symmetric Local Binary Convolutional Neural Networks |
| TCS-LBP | - Threshold Center-Symmetric Local Binary Patterns |
| ULBP | - Uniform Local Binary Patterns |

# CHAPTER 1

# INTRODUCTION

## 1.1 Overview

Handwriting recognition is a challenging problem due to the exponential development of technology. Handwriting recognition is categorized into two kinds, online and offline, based on the input method to the system. The applications that use the online form receive the input by moving the pen on a pen-based screen, while the offline applications use the image captured using an interface such as a scanner or camera [1]. Many applications need an automatic recognition system to recognize handwritten images with high accuracy and speed, such as postal code, bank checks reading in offline systems and editors, enjoyment applications in online systems. Nowadays, the interest in script and language identification is growing for multilingual and bilingual scripts due to their different forms and styles [2]–[5].

Furthermore, the digit and character forms vary from one language to another, leading to build different handwriting recognition systems. In many studies, English digit and character recognition have been examined for four decades [6]-[7], while Arabic digit and characters have been investigated in the Nineties. After that, many studies on Arabic handwriting recognition have been done using different Arabic handwritten datasets that include some challenging writers' styles.

Moreover, Arabic and English handwritten digit recognition is a challenging problem because the writing style differs from writer to others and the variation of style at different instances of the same writer. Because of these reasons, many studies were proposed to address either Arabic [8]–[11] or Latin [12]–[16] character/digit recognition problems. In contrast, none of the research focused on bilingual Arabic-

Latin character/digit systems except those developed for discriminating between the languages of documents/scripts [17]-[18].

In addition, some languages are universal such as English, Arabic, Spanish, etc. These languages are considered as a second language in countries where their language is not one of the universal languages. They need the second language because of one of the following reasons: religious reasons, when their holy books were written in a different language like the holy Quran in some Islamic countries (i.e., East Asian countries), educational reasons when references or lectures were written or explained in another language and social reasons when people visit other countries. Due to these reasons, bilingual scripts have been used in some countries.

Further, many commercial forms, including opening bank accounts, bank checks, and handwritten sales invoices, can be written in bilingual forms. For example, a customer can fill an opening bank account form using Arabic, while another can fill it in English. Also, others can use both languages to fill the form. Figure 1.1 shows three samples of filling the form using either Arabic digits, English digits, or both. Therefore, in this case, the operation in the bank needs two systems to recognize the digits, one for Arabic and the other for English. Using such two systems consumes the resources and requires user interaction to move from one language to another, requiring more users' time and effort. Thus, bilingual handwriting recognition systems are needed in real applications instead of using two systems, which is a less practical solution.



(a)

(b)

(c)

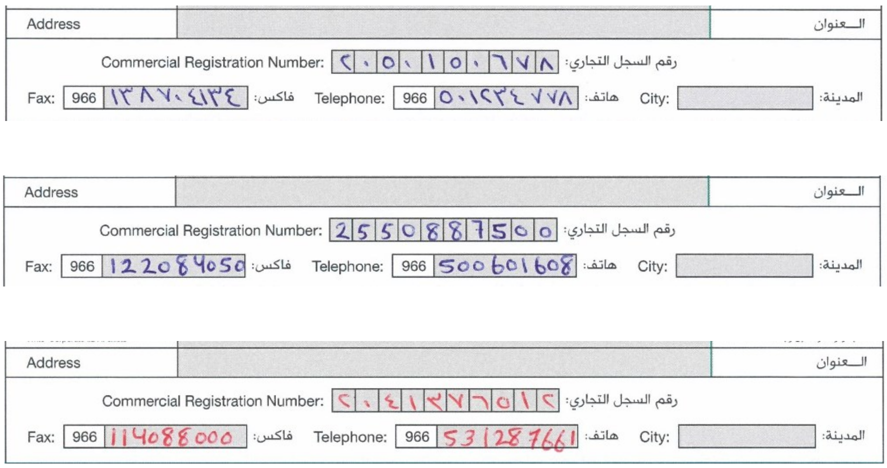


Figure 1.1: Samples of filling an opening bank account form (a: filling form using Arabic), (a: filling form using English), (a: filling form using bilingual)

## 1.2 Research Background

Handwriting recognition is a task done by a machine to interpret understandable handwritten input from photographs, touch screens, and other devices. Many computer applications need an automatic recognition system to recognize handwritten images with high accuracy and speed, such as searching for words, sub-words, or numbers in large volumes of documents, automatic sorting of postal mail, and convenient editing of previously printed documents, postal code, and bank checks reading in offline system and editors, and enjoyment applications in online systems.

Many studies proposed systems to allow a computer to recognize handwritten scripts using statistical approaches or machine learning algorithms. These systems receive a digit, character, word, or/and text image as input and classify it to its corresponding label. However, only a few of them consider bilingual scripts. Researchers are not concerned deeply about bilingual recognition of Arabic-Latin digits, although it is a significant issue, especially in the middle east. Most public and government documents in Arabic states are typed or written in bilingual forms (i.e., mixed of Arabic and English) such as application forms, railway reservation slips, and cheques that need applications that support bilingual involving handwriting recognition systems.

Furthermore, several studies applied statistical approaches for digit classification. Linear Discriminant Function (LDF) is an example of this approach applied to the Latin digit dataset [19]. Quadratic Discriminant Function (QDF) is another statistical approach that was modified to produce the Modified Quadratic Discriminant Function (MQDF) [20]. Moreover, Learning Quadratic Discriminant Function (LQDF) [21] is proposed based on the QDF technique that merges the power of MQDF and neural classification. Additionally, a Discriminative Learning Quadratic Discriminant Function (DLQDF) [7] and Graphical Lasso Quadratic Discriminant Function (GLQDF) [20] are modified versions of QDF that GLQDF uses the graphical lasso approach to find the covariance instead of using the Maximum-Likelihood Estimation (MLE). Further, generative models used in [22], multi statistical approach in [23], Gaussian Mixture Models (GMM) in [24], and

Naive Bayesian (NB) classifier used in [25]-[26] are other statistical-based techniques.

In addition, many machine learning techniques were utilized, such as Support Vector Machine (SVM), Neural Networks (NN), decision trees, etc., for handwritten recognition [27]–[30]. A random forest classifier is a large collection of tree classifiers [31]. This classifier aims to averaging noisy and unbiased models to build models with low variance in terms of classification. Each tree classifier is grown in random form. The advantages of the random forest classifier are that it is suitable for extensive data, deals with missing values present in the data, does not require normalizing data as it uses a rule-based approach. However, it needs many resources to build numerous trees to combine their outputs, is hard to interpret the results and fails to determine the significance of each variable, and can be unreliable with deep trees. Moreover, it suffers from overfitting because of the randomized trees. It needs much focus on the subsampling phase that has a role in random forests algorithm and may need to be tuned more carefully than other parameters [31]–[33].

Further, Support Vector Machine (SVM) is a classification approach used to classify linear or nonlinear data. The first work using SVM was proposed by [34]. The idea of using SVM is based on statistical learning theory [35]. In general, the idea of this classifier is by separating the data set of two classes with a maximum distance between them. SVM was applied for developing handwritten digit recognition models with several feature extraction techniques, including Local Binary Pattern-based techniques [27], sliding window approach [28], projections histograms [29] [36], rule-based reasoning approach [36]; ring-zones, and Kirsch features [37]; and Histogram of Oriented Gradient (HOG) [38].

Likewise, SVM was fused with other techniques to produce hybrid models that provide more accurate models for classifying digits. Multilayer Perceptron (MLP) was fused with SVM [39], Bat algorithm as a swarm intelligence algorithm was combined with SVM [40], and unbalanced decision tree [41]. Nevertheless, SVM is not suitable for large datasets and does not perform well when the classes in the data set overlap. Also, it does not work well if the number of features for each data point exceeds the number of training data samples and may be affected by the presence of missing data [32]-[33] [42]-[43].

Furthermore, Neural Networks (NN) is a widespread machine learning approach applied to handwritten recognition [44]–[46]. MLP classifier is an NN technique used for image classification problems and built using a back-propagation algorithm [47]. The network's input layer receives the features or the variables extracted from training data. The input of hidden layers and output layer is the weighted sum of the outputs from the previous layer. The strengths of NN are the ability to deal with large volumes of data [32]-[33][48], no need to the prior knowledge of the data generating process, and no specific architecture used due to the ability of the network to learn the hidden relationship in the data [49].

However, the disadvantages of NN are the difficulty of listing out all possible NN architecture, and it causes the difficulty to find the optimal architecture, hard to interpret the results, needs comprehensive cross-validation to confirm validity [32]. Moreover, using too many hidden layers causes the overfitting problem and is time-consuming [49]. Additionally, the three most famous NN approaches are Deep Neural Network (DNN), Deep Belief Network (DBN), and Convolutional Neural Network (CNN) [46].

Nowadays, deep learning approaches are considered the hot trend of the new research that composes many non-linear information processing layers. The main groups of deep learning techniques are defined based on the architectures and the purpose, such as synthesis or classification [50]. One common deep learning technique called CNN is a type of feed-forward neural network that uses three architectural ideas, including local receptive fields, weight sharing, and pooling layers or sub-sampling [51]. Although CNN gives astonishing outcomes [13]–[15] [52]–[57], it suffers from a considerable time complexity due to the need for many hidden layers, and when deeper networks can start converging, a degradation problem is exposed, or when the network depth increases, accuracy gets saturated (which might be unsurprising) and then degrades rapidly [58]. This drawback motivates researchers to suggest many versions or modifications of CNN, including Deep Residual Network (ResNet). ResNet is one of the common variations of CNN that needs less computational complexity than CNN and addresses the degradation problem [58]. However, it still needs a large number of learnable parameters.

On the other hand, LBP [59] is one of the common texture descriptors used in many studies due to its resistance to lighting changes and low computational complexity [60]–[62]. The LBP technique converts an image's pixels' value to a binary number based on a threshold value. This threshold value is the center pixel of a block of pixels [63]-[64]. Further, many versions of LBP were proposed to improve the performance of the LBP systems, including Uniform Local Binary Patterns (ULBP) [65], Center Symmetric Local Ternary Patterns (CS-LTP) [66], center-symmetric local binary patterns (CS-LBP) [67], etc.

As reported in [67], CS-LBP is more efficient for tolerance to illumination changes and computational simplicity and is used as a keypoint descriptor. The illumination change is challenging for character classification problems [68]. This problem is related to the digit images captured under several illumination conditions causing illumination variations, including changes in lighting, shadows, or noise. For example, the car plate is captured under the sun from various directions. In general, object surfaces appear different in different lighting conditions. Depending on the direction in which it reflects, the reflectance of a material tells us how much light is absorbed. The object's appearance changes according to the position of the camera and the illumination of the object.

In addition, CS-LBP can detect the keypoints and estimate the local patch around the keypoints. Moreover, CS-LBP has higher stability in the flat image region and is closely related to gradient operator that considers gray-level differences between pairs of opposite pixels in a neighborhood. CS-LBP is two times faster than LBP, and the probability of getting a 0 value does almost not happen [69].

Fusing LBP with CNN generates another version of CNN called Local Binary Convolutional Networks (LBCNN) [15] that reduces the learnable parameters that CNN suffers from. LBP has been formulated as a convolution layer called Local Binary Convolution (LBC). The LBC layer has several parts, including a set of fixed scattered binary convolutional filters (called anchor weights), a non-linear activation function, and a set of learnable linear weights. The significant difference between the LBC and CNN is that LBC has fewer learnable parameters than CNN [15]. However, LBCNN suffers from some limitations discussed in the next section.

Generally, in CS-LBP, each center-symmetric pair of pixels is compared instead of comparing each pixel to the center pixel used in LBP. Moreover, CS-LBP has higher stability in the flat image region and is closely related to gradient operator that takes into account gray-level differences between pairs of opposite pixels in a neighborhood [69]. The advantages of the CS-LBP motivate this research to propose a new CNN-based model fused with the CS-LBP technique called center-symmetric local binary convolutional networks (CS-LBCNN). Although CS-LBP detects the key points by comparing each center-symmetric pair of pixels, the comparison process is restricted by subtracting a pixel from the other and applying a zero-thresholding function. This restriction enforces the CS-LBP to be encoded in only one way that may straiten the CS-LBP descriptors. A modified version of CS-LBP called threshold center-symmetric local binary patterns (TCS-LBP) is proposed to address such an issue. CS-LBP is fused with CNN to produce an enhanced version on CS-LBCNN called threshold center-symmetric local binary convolutional networks (TCS-LBCNN). In TCS-LBCNN, non-zero values are applied as thresholds instead of the zero-value of CS-LBCNN, explained more in Section 4.3 (Chapter 4).

## 1.3 Problem Statement

Many official documents are written in the bilingual form in most middle east countries, such as bank forms, invoices, memos, etc. One scenario has been presented to show the need for a bilingual digit recognition system using Figure 1.1, which shows some samples of used forms. Presently many studies were proposed in handwritten digit recognition either in Arabic [8]–[11] or Latin [12]–[16]. However, none of the research focused on bilingual Arabic-Latin digits to provide such a system. Consequently, bilingual handwriting recognition systems are required in many real applications, as mentioned in Section 1.2.

Furthermore, CNN is the core of the image-based deep learning model used in many applications and modified in some research, including ResNet and LBCNN. The main drawbacks of the CNN model can be summarized as follows, it needs more computational complexity, and when deeper networks start converging, a degradation problem has been exposed [58]. Therefore, the ResNet technique was proposed to reduce the complexity of CNN and address the degradation problem but still needs more learnable parameters. Hence, LBCNN was introduced to overcome the drawback of the ResNet by applying the LBC layers [15]. LBCNN uses eight

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