ENSEMBLE LEARNING USING MULTI-OBJECTIVE OPTIMISATION FOR ARABIC HANDWRITTEN WORDS

HAITHAM QUTAIBA GHADHBAN

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DEDICATION

My utmost thanks and gratitude must first be offered to Almighty Allah for all his blessings, and in granting me good health throughout the duration of this research.

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ABSTRACT

Arabic handwriting recognition is a dynamic and stimulating field of study within pattern recognition. This system plays quite a significant part in today's global environment. It is a widespread and computationally costly function due to cursive writing, a massive number of words, and writing style. Based on the literature, the existing features lack data supportive techniques and building geometric features. Most ensemble learning approaches are based on the assumption of linear combination, which is not valid due to differences in data types. Also, the existing approaches of classifier generation do not support decision-making for selecting the most suitable classifier, and it requires enabling multi-objective optimisation to handle these differences in data types. In this thesis, new type of feature for handwriting using Segments Interpolation (SI) to find the best fitting line in each of the windows with a model for finding the best operating point window size for SI features. Multi-Objective Ensemble Oriented (MOEO) formulated to control the classifier topology and provide feedback support for changing the classifiers' topology and weights based on the extension of Non-dominated Sorting Genetic Algorithm (NSGA-II). It is designated as the Random Subset based Parents Selection (RSPS-NSGA-II) to handle neurons and accuracy. Evaluation metrics from two perspectives classification and Multi-objective optimization. The experimental design based on two subsets of the IFN/ENIT database. The first one consists of 10 classes (C10) and 22 classes (C22). The features were tested with Support Vector Machine (SVM) and Extreme Learning Machine (ELM). This work improved due to the SI feature. SI shows a significant result with SVM with 88.53% for C22. RSPS for C10 at k=2 achieved 91% accuracy with fewer neurons than NSGA-II, and for C22 at k=10, accuracy has been increased 81% compared to NSGA-II 78%. Future work may consider introducing more features to the system, applying them to other languages, and integrating it with sequence learning for more accuracy.

ABSTRAK

Pengenalan tulisan Arab merupakan bidang yang dinamik dalam teknologi pengecaman corak yang amat signifikan pada zaman globalisasi ini. Fungsi ini semakin berleluasa tetapi berkos tinggi disebabkan faktor-faktor seperti penulisan kursif, kosa kata yang luas, serta gaya penulisan. Ciri-ciri dalam kebanyakan literatur kekurangan teknik sokongan data dan pembinaan ciri geometri. Kebanyakannya berasaskan andaian gabungan linear adalah tidak sah kerana perbezaan antara jenis data serta kesukaran pemilihan pengelas yang paling sesuai. Pembolehan pengoptimuman multi-objektif diperlukan untuk mengawal perbezaan jenis data ini. Tesis ini memperkenalkan jenis ciri yang baru dengan Interpolasi Segment (SI) bagi menentukan garis yang paling tepat dalam setiap window dengan model pencarian saiz window yang paling tepat sebagai titik operasi untuk ciri SI. Ensembel Berorientasi Multi-Objektif (MOEO) dirumuskan untuk mengawal topologi pengelasan dan menyediakan sokongan maklumbalas untuk mengubah topologi dan pemberat berdasarkan sambungan pengoptimuman Penyusunan Genetik yang Tidak Didominasi (NSGA-II). Ia ditetapkan sebagai Pemilihan Ibu Bapa berdasarkan Subset Rawak (RSPS-NSGA-II) bagi menangani bilangan neuron dan ketepatan. Matriks penilaian daripada perspektif klasifikasi dan pengoptimuman multi-objektif. Eksperimen ini direka berdasarkan pangkalan data IFN/ENIT, 10 kelas (C10) dan 22 kelas(C22) yang diuji dengan Mesin Sokongan Vektor (SVM) dan Mesin Pembelajaran Ekstrem (ELM). Peningkatan prestasi ini disebabkan ciri SI yang menunjukkan keputusan signifikan dengan SVM, iaitu 88.53% untuk C22. RSPS untuk C10 pada k=2 mencapai ketepatan 91% dengan lebih kurang bilangan neuron berbanding NSGA-II, manakala C22 pada k=10, ketetapan meningkat ke 81% berbandingkan NSGA-II, 78%. Penyelidikan selanjutnya harus mempertimbangkan pengenalan lebih ciri dalam sistem, dan mengaplikasikan ciri tersebut untuk bahasa lain serta berintegrasi dengan pembelajaran berurutan bagi meningkatkan ketepatan.

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LIST OF SYMBOLS AND ABBREVIATIONS

OCR	–	Optical Character Recognition
MSA	–	Modern Standard Arabic
SI	–	Segments Interpolation
MOEO	–	Multi-Objective Ensemble-Oriented
NSGA-II	–	Non-Dominated Sorting Genetic Algorithm-II
RSPS	–	Random Sub-Set based Parents Selection
HMM	–	Hidden Markov Model
GHT	–	Generalised Hough Transform
CNN	–	Convolutional Neural Network
LSTM	–	Long Short-Term Memory
WFST	–	Weighted Finite-State Transducer
PDA	–	Personal Digital Assistant
RNN	–	Recurrent Neural Network
SVM	–	Support Vector Machine
GRU	–	Gated Recurrent Unit
MCDNN	–	Multi-Column Deep Neural Networks
SIFT	–	Scale Invariant Feature Transform
HOG	–	Histogram of Oriented Gradients
DWT	–	Discrete Wavelet Transform
SCF	–	Statistical and Contour Based Feature
ZER	–	Zernike moments
PCVM	–	Probabilistic Classification Vector Machines
PSI-BLAST	–	Position-Specific Iterated Basic Local Alignment Search Tool
FCM	–	Fuzzy C-Means

EER	–	Error Function
CM	–	Chebyshev moment
FOCM	–	Fractional-Order Chebyshev Moments
FOCMI	–	Fractional-Order Chebyshev Moment Invariants
EEG	–	Electroencephalogram
MLP	–	Multi-Layer Perceptron
ELM	–	Extreme Learning Machine
FFNN	–	Feed Forward Neural Networks
SLFN	–	Single Hidden Layer Feed-forward Neural Networks
SHFYN	–	Single Hidden Forward Layer Neural
OIAHCR	–	Offline Isolated Arabic Handwriting Character Recognition
FFT	–	Fast Fourier Transform
MR	–	Max Rule
GWAR	–	General Weighted Average Rule
MA	–	Max Average
AMR	–	Average Max Combination
RDA	–	Regularised Discrimination Analysis
DST	–	Dempster-Shafer theory
PSO	–	Particle Swarm Optimisation
GA	–	Genetic Algorithm
GSA	–	Gravitational Search Algorithm
PF	–	Pareto Front
KNN	–	K-Nearest Neighbours
TP	–	True Positive
TN	–	True Negative
FP	–	False Positive
FN	–	False Negative
NDS	–	Number of Non-Dominated Solution
MOO	–	Multi-Objective Optimisation
TDNN	–	Time Delay Neural Network

RNN	–	Recurrent Neural Network
DCNN	–	Deep Convolutional Neural Network
MFCC	–	Mel Frequency Cepstral Coefficients
DBN	–	Deep Belief Network
DRL	–	Deep Reinforcement Learning
DNN	–	Deep Neural Network
NN	–	Nearest Neighbour
ANN	–	Artificial Neural Network
NB	–	Naïve Bayesian
HAS	–	Harmony Search Algorithm
RF	–	Random Forest
W-TSV	–	Weighted Topological Signature Vector
DAG	–	Directed Acyclic Graph
ARG	–	Attributed Relational Graph
RBF	–	Radial Basis Function
DL	–	Deep Learning
PSSM	–	Position-Specific Scoring Matrix
MPSO	–	Multi-phase Particle Swarm Optimisation
HNB	–	Hierarchical Naïve Bays
MOP	–	Multi-Objective Optimisation Problem
NRSGA	–	Non-dominated Rank Sorting Genetic Algorithm
SVR	–	Support Vector Regression
PDIP	–	Primal-Dual Interior-Point
MOLA	–	Multi-Objective Land Allocation

LIST OF APPENDICES

LIST OF PUBLICATIONS

1. Ghadhban, H. Q., Othman, M., Samsudin, N. A., Ismail, M. N. B. & Hammoodi, M. R. (2020). Survey of offline Arabic handwriting word recognition. In *International Conference on Soft Computing and Data Mining* (pp. 358-372). Springer, Cham.
2. Ghadhban, H. Q., Othman, M., Samsudin, N., Kasim, S., Mohamed, S. A. & Aljeroudi, Y. (2021). Segments Interpolation Extractor for Finding the Best Fit Line in Arabic Offline Handwriting Recognition Words. *IEEE Access*, *9*, 73482-73494.
3. Ghadhban, H. Q., Othman, M. & Samsudin, N. A. (2021). analysis of feature extraction and classification for offline arabic handwriting word recognition. *Journal of Engineering Science and Technology*, *16*(3), 2719-2735.

CHAPTER 1

INTRODUCTION

1.1 Research Background

Handwriting recognition is a dynamic and stimulating field of study within pattern recognition and plays quite a significant part in today's global environment. It is a prevalent and computationally costly function (Yadav, 2015). It is not easy to understand the true meaning of handwritten texts in today's world. There are several aspects where have to identify the letters, words, and digits, such as bank cheques Al-Nuzaili *et al.* (2018), postal addresses Gopikrishna & Samatha (2018), and handwritten form processing Barrus *et al.* (2018) where handwriting recognition is necessary.

A graphical representation of handwritten recognition is available. It refers to converting the spatial and temporal aspects of writing into a symbol that can be recognised both offline Chen *et al.* (2017), and online (Alipour *et al.*, 2016). Optical Character Recognition (OCR) is an associated term, and it means converting text from scanned images, written text, or handwritten text into machine-readable text. Handwriting recognition is limited to the recognition of handwritten text. Figures 1.1 (a) and 1.1 (b) illustrate handwritten words and their corresponding recognised version.

(a) (b)

Figure 1.1: (a) Original image (b) recognised text

In the past few decades Bhunia *et al.* (2018), much research has been conducted about handwriting recognition, particularly for the Latin script (Singh, P., 2018). Notably, there are quite good results for machine printed text recognition with over 99% accuracy for the renowned IAM handwritten text dataset for the Latin script (Marti & Bunke, 2003). However, only minor studies have been conducted in Arabic handwritten recognition as against Latin (Lawgali, 2015). Due to the intricacy of Arabic text and poor databases (Alkhateeb, 2015). Recognition of Arabic text is in the initial phases compared to the recognition of Chinese, Latin, and Japanese manuscripts.

Furthermore, there is a big challenge in Arabic writing recognition practices that arise from the data's cursive form. Recognising Arabic handwritten content is quite challenging. This challenge arises from several aspects, like the Arabic writing setup that is cursive, the pen, the writing style, and other elements.

There are few types of research works for unconstrained Arabic handwritten text recognition that has been published (Rabi *et al.*, 2017a). The majority of the studies on Arabic handwriting recognition have tackled isolated character, word or digit, (Jayech *et al.*, 2016a; Younis 2017; Alani, 2017). Hence, there is much research needs to be accomplished in Arabic handwritten text recognition. Academics have found many kinds of challenges in recognising Arabic handwriting (Aloud, 2018). The following section, discuss several of the challenges related to Arabic handwriting recognition.

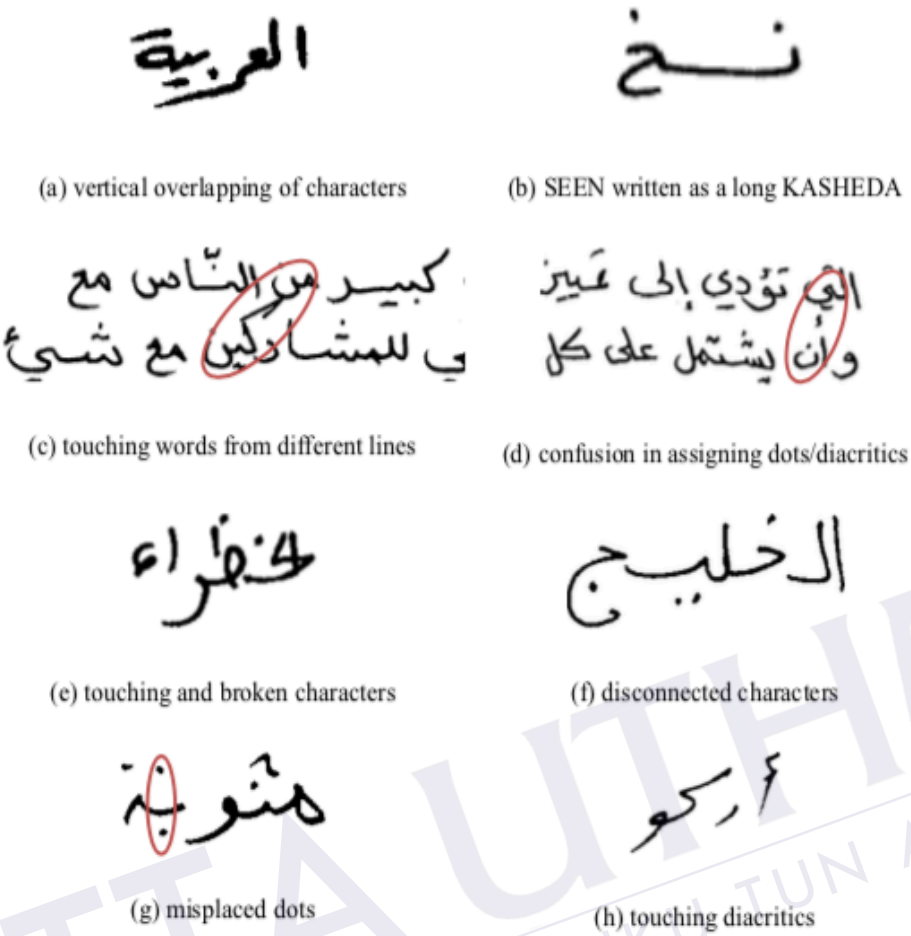

Figure 1.2: Illustration of some irregularities present in Arabic handwriting (Parvez, 2010)

- The Arabic language is written in cursively forms Rabi *et al.* (2018a), with overlapping characters. Due to these overlapping characters, separation of words in Arabic handwriting is difficult and needs to utilise the contextual information in many cases. Moreover, the overlapping of characters makes the assignment of dots or diacritics a challenging task. As shown in Figure 1.2(a), it is not easy to decide which characters the dots belong to without contextual information.
- Arabic handwriting contains a lot of ligatures (like لا). Some of these ligatures are optional (like لحـ/لح). Ligatures are difficult to segment into component characters and may be treated as different characters.
- Writing styles have a bad effect in some cases. For example, SEEN (ـسـ) is sometimes written as a long KASHEDA Figure 1.2(b), making it very difficult

to recognise it without a contextual/dictionary. Other examples include the different writing dots, confusion between double-dots, and madda (~).

- Many Arabic characters have ascenders and descenders characters which means the words, not on the same baseline. Sometimes, ascenders and descenders of words from different lines touch each other Figure 1.2(c). In addition, gaps between the lines on a page may not be uniform and written straight as in the text, which is a general handwriting recognition problem. In many cases, dots/diacritics are written in between two lines. Assigning these dots/diacritics to the correct words requires contextual information Figure 1.2(d). Other cases of irregularities in Arabic handwriting include touching and broken characters within a word Figure 1.2(e), disconnected characters within a word Figure 1.2(f), misplaced dots Figure 1.2(g) and touching diacritics Figure 1.2(h).
- There are also some other issues that the researchers in Arabic handwriting recognition have to deal with, for example, difficulties due to the writing process and scanning. Since the scanning process may introduce noise from the scanner bed-page border, these issues and difficulties make Arabic word decomposition into letters a very delicate process and not always ensured (Aloud, 2018). Many approaches and techniques developed for other languages cannot be applied directly to the Arabic script. Therefore, techniques for Arabic handwriting recognition are expected to consider these challenges of Arabic script.

Arabic offline handwriting recognition is a highly important research topic due to different challenges such as the cursive nature of writing, the connectivity between the Arabic letters, the huge number of Arabic words over 12 million, the different styles of writing, and the variation of various factors which makes the problem of recognition of Arabic words hard and challenging (Jemni *et al.*, 2018b). Researchers have tackled this problem in different ways. Some of them have aimed to improve the pre-processing of the manuscripts (Metwally, Khalil & Abbas, 2017). Others have developed approaches for segmenting the letters (Ghaleb, Nagabhushan & Pal, 2017). Others have focused on handcrafted feature extraction Amrouch, Rabi & Es-Saady (2018), and others have worked on the classification layer by optimising classifiers or

developing approaches for combining them (Tamen, Drias & Boughaci, 2017).

In this thesis, two phases are considered: feature extraction based segmentation and ensemble learning that have an enormous impact on recognition rate. In the first phase, several studies have used different techniques for geometrical feature extraction and showed a good performance in recognizing Arabic words (Chherawala & Cheriet, 2014). Aouadi *et al.* (2016) applied segmentation on touching characters, and Li (2013) used to divide words horizontally. Other techniques have been used in recognising handwriting, such as zoning method based features Rani & Vasudev (2016) and sliding windows in different directions (Al-wajih & Ghazali, 2020). The sliding window technique has been used for extracting local structural or statistical features, (Alkhateeb *et al.*, 2009; Khémiri, Kacem & Belaïd, 2014). The structural features describe the topological and geometrical characteristics of the word. They include ascendants, descendants, loops, diacritics and their position relative to the baseline. All these previous studies were based on drawing the characteristics of the letters and lacking supportive data techniques such as regression or interpolation.

In the second phase, ensemble learning is that a combination of several models leads to a potentially reduced error level compared to a single classifier, thereby enhancing the model's predictive performance (Sagi & Rokach, 2018). Many of the ensemble methods that researchers adopt follow certain non-valid assumptions. For example, the weighted average rule of Tsai *et al.* (2018) assumes that the overall performance of combining sets of classifiers based on their training accuracy is optimal, which is not valid due to the non-linear, non-stationarity nature of the data-class distribution. Most studies have focused on accuracy only, which is the lack of control in the classifier's topology and its lack of feedback support for changing the classifiers' topology and weighting on the other side. Hence, a multi-objective needs to be consider to optimise the prediction of more than one perceptive, such as time, computational and other factors that are related to classifiers. This method will handle performance from the perspective of accuracy and efficiency to have a lightweight recognition model.

Overall, accuracy plays the most important measure value to analyse the performance at different phases. Each of these phases has its challenges and difficulties. For example, the segmentation of the text into lines is a challenging task itself, such as the curvy text lines, non–uniform gaps between the lines, dots, or

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