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SYSTEMATIC LITERATURE REVIEW ON FEATURE RANKING METHODS TO DETERMINE HANDWRITING RECOGNITION

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ABSTRACT

Features ranking is a very essential step in determining significant features for handwriting images. Its goal is to increase the classification performance by reducing the computational cost. In the context of handwriting recognition, the extraction of image features can lead to the problem of high dimensionality of data. This has become the handwriting recognition problem whereby the variation of generated features are contributing to the factor of irrelevant or redundant features while maybe even correlated to each other that burden the classification process. As a result, this will be contributing to the lower identification performance accuracy due to the increase of computational complexity. This paper used a Systematic Literature Review (SLR) to compile the features ranking based technique to overcome the drawbacks above. SLR is a literature review that collects and critically analyzes multiple studies to answer the research question. Five research questions were drawn for this purpose. Information such as techniques, collection of datasets and methods' performances were extracted from 52 articles. This information was analyzed to identify the strengths and weaknesses of the techniques and the affecting elements to the performance of features ranking. The SLR has also found out that some of the studies were using feature selection methods in handwriting recognition. The efficiency of some feature selection methods has exceeded other approaches, even though it is only at a reasonable level. Therefore, more studies are needed to overcome the drawbacks of the handwriting recognition by using features ranking.

Keywords: *Feature Extraction, Features Ranking, Feature Selection, Handwriting Recognition*

1. INTRODUCTION

In the scope of handwriting recognition, the selection of a relevant set of features to represent data samples is one of the key factors that affect the performance. The extraction of handwriting usually will result in a pool of features. This has resulted in the creation of a wide range of feature sets. The use of a higher number of features can reduce the classification accuracy due to the presence of irrelevant and redundant features [1] [2] [3]. This can also lead to a question on how to figure out if the selected features might be dependent on other features. The use of too many features can be a disadvantage as it reduces the speed of the process and increases data redundancy.

To identify the writer, it is crucial to search for an optimal set of features and use them to reduce features and diminish large data scale [2]. Thus, the optimal approach in determining the discriminatory features is features ranking techniques. Features ranking reduces the dimensionality of the feature space and excludes obsolete, incompatible features. This led to increasing the performance of the classification process, improving the data quality, speeding up the learning time and increasing the comprehensibility of the results [4] [1]. Thus, the multiple features ranking techniques are best to be explored to find their suitability and capability to rank and score level of significance for features of handwriting image to solve the said problem.

The purpose of this systematic literature review is to collects multiple and critically analyze information about the features ranking methods to overcome the problem. Information such as technique, collection of datasets and classification performance were extracted from the research. This information was analyzed to identify the strengths and weaknesses of the methods and the affecting elements to the performance of features ranking. Thus, from the analysis it is helped to suggest the selection of the best two or more features ranking methods to be fusion to determine the most significant features based on ranking.

This paper consists of 8 sections. In Section 2, the validity of proposed are discussed. For the related work, this paper will discuss in the Section 3 and the method of undertaking this study will be discussed in detail in Section 4. Section 5 explains and addresses the findings of this study. The research limitation is explained in Section 6 while the conclusion of SLR will be described in Section 7. Finally, the future work is presented in Section 8.

2. VALIDITY OF PROPOSED

The selection of an appropriate feature is one of the primary elements impacting the achievable performance in the context of handwriting recognition. The computational cost will be affected by the usage of many characteristics. As a result, feature ranking methods are utilized to find the best and most applicable characteristics. Feature ranking approaches are less computationally costly because they apply the criteria to each individual feature before evaluating the efficacy of all the features using the results [1]. As a result, each characteristic is ranked in order of importance based on the values.

Features ranking are also known with the simplicity and higher rate of success in handwriting recognition [5]. The main purpose of this SLR is to review different method in features ranking because each features ranking are producing the different ranking according to their own criterion.

3. RELATED WORK

Features ranking is currently an active area among researchers in different topics such as data mining, pattern recognition and machine learning [4]. Features ranking help to understand the features easily, reduce the computational cost, reduce the impact of dimensionality curse and increase the efficiency of classification performance [5]. It is a valuable technique especially for datasets that contain hundreds to tens of thousands of variables or features. Features ranking technique is used to choose the best subset of features in HMM-based recognition systems by matching the sequence of extracted features with the lexicometries [6]. In another research, two features ranking methods which are Fisher Score and Info Gain Attribute Evaluation are applied in the authentication system for verification or identification of the writer by using password handwriting [7]. Random forest classifiers associated with emotional state are built to identify negative emotions such as stress and depression. Features ranking is implemented to identify which features reveal the emotional state [8].

The Handwriting Recognition is divided into two types which are on-line and off-line recognition. The time-ordered sequence of coordinates representing the rotation of the tip of the pen are reported in the on-line recognition while only the representation of the text in off-line mode [9]. There is a lot of work going on in regard to Handwriting Recognition. In [10], it proposes a new method for the Hidden Markov Tree (HMT) model which compares the wavelet coefficient with the Gabor filter. In the other research [11], local character-based codebooks and global codebooks are generated by using Otsu algorithms. The variation of shape in features, enveloped curves and outer boundary gradient information that are used to demonstrate the combination of three novel features for identification through Multiple Kernel Learning (MKL) integrated into genetic algorithms was suggested by [12]. In the latest research by [13], it proposed to use the usage of run length display features either through the sets of white, black or white and black pixels in four directions to identify a writer when utilizing multi-script handwritten text.

A non-iterative calculation on the dataset is implied by the feature ranking approach, which is substantially quicker than a classifier training session. Furthermore, feature ranking methods assess the data's inherent qualities rather than the data's interactions with a specific classifier. As a result, the answers presented should be more comprehensive and applicable to a broader classifier family. One of the limitations of ranking systems is that there is no universal criterion for selecting the feature space dimension [1]. This means that deciding on a cut-off point for the amount of characteristics to be picked is challenging.

Furthermore, the feature subset chosen may not be ideal, since essential features that are less helpful on their own but extremely revealing when paired with others may be overlooked.

The feature selection method is critical for achieving adequate performance in the field of handwriting recognition [53] [54]. As is well known, variances in writing styles caused by a number of factors such as age, culture, level of education, and origin result in a huge amount of form diversity, which has led to the development of a wide range of feature sets. Many features extraction and feature selection strategies have been developed to deal with such unpredictability and manage the growing number of accessible features.

The goal of this research is to use the principles of feature ranking algorithms to create an experimental strategy for selecting the feature subset that will yield the best classification results. We apply the feature ranking approach to choose feature subsets, as stated in the introduction.

4. METHODOLOGY

The systematic literature review method is to identify, evaluate and summarize related research regarding the research question and field of studies [14]. A systematic literature review has three steps. The first step is planning, the second step is conducting, and the third step is reporting. Figure 1 provides detailed information about the three steps.

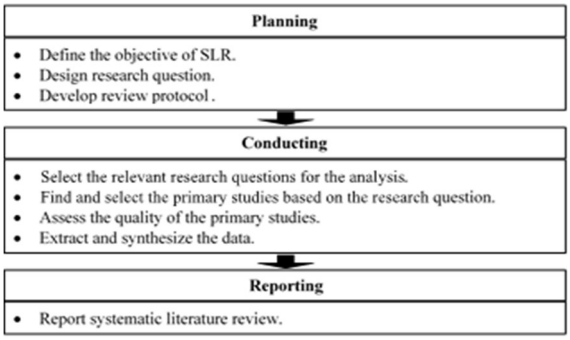

Figure 1: The Process of Systematic Literature Review

The objectives were designed in the planning steps to identify the steps in features extraction, to identify the techniques used in features ranking and to identify the affecting elements to the performance of features ranking. An important step is the development of a review protocol to achieve the objectives [15]. In the review protocol, the question has been specified. Moreover, the database to be searched and the method to be used to identify, assemble, and assess the evidence are also in the review protocol [16]. After the planning steps, the important questions have been figured out and prioritized consequently to extract the correct data in the conducting the steps. Finally, in the reporting steps, all related research and important details have been presented accordingly.

2.1 Research Question

The most important step in this SLR is to specify research questions. Research questions lay the foundation for this SLR. The SLR evaluates the proofs from various research findings in the features ranking and feature extraction techniques. The aims are to identify the steps of handwriting recognition, to gather the techniques and study the affecting elements to the performance of features ranking. The research question and its motivations are described in Table 1 below.

Table 1 Research Question

#	Research Question	Motivation
RQ1	What are the common steps in handwriting recognition?	Identify the common step in handwriting recognition
RQ2	What are the techniques and datasets used in features extraction?	Identify the techniques and datasets used in features extraction
RQ3	What are the techniques used in features ranking?	Identify the techniques used in features ranking
RQ4	What are the strengths and weaknesses of the features ranking?	Assess the strengths and weakness of the features ranking
RQ5	What are the classifiers used in handwriting recognition?	Identify the classifiers use in handwriting recognition

2.2 The Search Strategy

The next step in systematic literature review is the concepts of search strategy. In the search strategy, all the reports about features ranking are gathered and retrieved. In this systematic literature review, the primary search keyword used "features ranking in handwriting recognition". For

an alternative search keywords "feature extraction" and "handwriting recognition" were used. All the keywords are taken from journal, textbooks, technical reports and conference proceedings. To limit the range of the searching, Boolean operators "OR" and "AND" also were used. The search also was limited by the year 200-2019 and the language used was English only. Below is the list of the digital database used in this systematic literature review:

- Science Direct
- IEEE Xplore
- Scopus
- Springer Link
- Google Scholar
- ACM Digital Library
- Semantic Scholar
- Research Gate

2.3 The Quality Assessment

Quality assessment includes additional information on the requirements for the inclusion and exclusion criteria. This explains the significance of primary research for the SLR. The SLR developed questionnaires to determine the validity and significance of the primary research, as shown in Table 3.

2.4 The Evaluation Criteria

The search of digital database produced a very wide result. To overcome the difficulties of processing the result, a scope is developed. A set of criteria known as inclusion and exclusion criteria to filter the review material in this systematic literature review are shown in Table 2. Next, the SLR applied the criteria in Table 2 and selects 50 articles as primary studies.

Table 2 Inclusion and Exclusion Criteria for SLR

Inclusion Criteria	Exclusion Criteria
1. Articles that were published 2014 until 2019.	1. Articles that were published before 2014
2. Articles that put features ranking as main discussion.	2. Studies which are not related to research question
3. Empirical study on features ranking for author's handwriting recognition.	3. Studies which are not related to author's handwriting recognition
4. Author's Handwriting Recognition	

2.5 The Data Extraction and Synthesis

The 50 chosen articles comply with the inclusion and exclusion criteria as described in Table 2. To discover the data, each article is reviewed carefully. Moreover, to collect information from the primary study, a form is designed. The data element to be derived is based on the research question set out in Table 3. The systematic literature review explained the purpose of each primary study, the proposed techniques, the repositories utilized, the variables and the performance of the proposed procedure.

Table 3 Quality Assessment Question

#	Question	Yes (1)	Partly (0.5)	No (0)
Q1	Are the goals of the studies clearly laid out?			
Q2	Does the studies explain the method proposed?			
Q3	Is the suggested approach clearly described?			
Q4	Does the study clearly describe data collection?			
Q5	Does the study identify the data groups of the experiment?			
Q6	Are the performance measures clearly defined to evaluate the proposed method?			
Q7	Are the results and findings stated clearly?			
Q8	Does the research carry out a comparative analysis of the proposed method?			
Q9	Did anyone cite the study?			

5. RESULT AND DISCUSSION

The systematic literature review has chosen 50 articles as primary studies that meet the criteria listed in Table 2. In Table 4, there are list of selected articles based on year published. These articles are classified into two groups which are primary articles and secondary articles. The meaning of primary articles are articles that put the features ranking method as one of the methods used for handwriting

recognition. Meanwhile, the secondary articles are articles that put the features ranking method as the main topic of discussion.

Table 4 Selected Primary Studies

Year	Primary Studies
2010	[17] [2] [11] [12]
2011	[18] [19]
2012	[20] [21]
2013	[13]
2014	[22] [15] [23] [24]
2015	[25] [26] [27] [4] [28] [3]
2016	[5] [29] [30] [31] [32] [33] [34]
2017	[35] [8] [36] [37] [38]
2018	[39] [16] [40] [41] [42] [43]
2019	[44] [1] [7] [45] [46] [47]

3.1 RQ1: What are the common steps in handwriting recognition?

There are two types of handwriting recognition which are Offline Handwriting Recognition and Online Handwriting Recognition [23] [43] [46]. Offline Handwriting Recognition are based on visual features and pixel information [46] [43]. Meanwhile, Online Handwriting Recognition uses sequence of writing order and instant temporal information [43] [46]. In handwriting recognition there are common sequence of steps [20]. Figure 2 shows the sequence of steps in handwriting recognition.

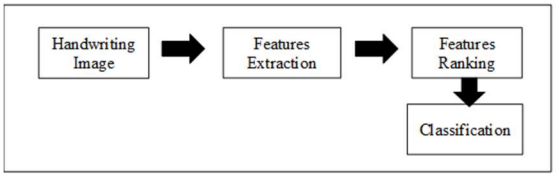

Figure 2: Sequence of Step in Handwriting Recognition

The data for this paper is the number of features extracted from handwriting images. In handwriting recognition system, feature extraction is the primary step. There are raw data signal in feature extraction process [8]. Feature extraction is a process which all features are extricated from each casing and taken into framework which convert them into a string of representative characters as proposed in [29]. In [9] [48], the feature extraction transformed the sequence of points into a sequence of feature vectors. Meanwhile, in this study [49], a collection of dimensional skeletons is collected by examining a fixed size window in various directions. In [18], the information that are gains from the feature extraction are pass to the matcher to assist in the classification process.

From Figure 2, the step after feature extraction is features ranking. Features ranking is a crucial step in handwriting recognition before the classification process. Features ranking reduce the computational cost and improve classification performance [5]. Moreover, features ranking increases the speed of data mining, enhance the quality of data and performance of data mining and increase the accuracy of mining results [50]. Features ranking is done by giving rank to features by evaluating each feature one by one according to some criterion that is proposed by [24]. In [4], features ranking incorporate picking features dependent on the scores of the element and scoring each element as indicated by a trait of the dataset associated with preparing while at that point picked features dependent on the score. Another researcher proposed the classification process is applied to the sorts database classes which sort from the nearest to the furthest based on the calculated rank [43]. Meanwhile in [1], the element positioning is adding features dynamically as indicated by their situation in the positioning and afterward select the features subset with expanding number of features.

The final step in handwriting recognition based on Figure 2 is classification. This step is important step for decision making. It uses the features that have been extracted from the feature extraction step to identify the text segments based on structural or statistical models. The machine learning techniques uses in this step are support vector machines (SVM), Artificial Neural Networks (ANN), Hidden Markov Models and K-nearest neighbors (k-NN) [51] [30]. In the study of [49], explains this step aims to distinguish the obscure word by utilizing the candidate characters of the HMM recognizer and the lexicon. In order to obtain improved recognition efficiency, [3] used a classifier mix instead of a single classifier, since the classifier that is good at classifying one class may not be good at classifying another class. The research in [29] proposed the feature sets are evaluated by recurrent neural network word classifier. The classifier is prepared for each feature set and provide decision in favor of its perceived word with all the votes are assembled utilizing a weighted vote conspire. Meanwhile, in [32] the classification is tested trough a vector quantization classifier and artificial neural network classifier.

3.2 RQ2: What are the techniques and data sets used in features extraction?

The selection of the feature extraction method is the most crucial step in the handwriting

recognition system to increase recognition accuracy. The purpose of feature extraction is to determine the efficacy of each strategy to collect useful information and hence resulting in more precise recognition results. There are many feature extraction methods in the handwriting recognition system. In [18], Discrete Cosine Transform (DCT) are used to extract the features from the Arabic handwritten words. The feature extraction method used in [20] is based on five feature extraction technique which are Box approach, Mean, Standard Mean, Standard Deviation, Center of gravity and projection profile features. The purpose of using more than one feature extraction techniques is to get more discriminative feature as possible. Moreover, feature extraction also can be done by supervised or unsupervised [29]. The most popular unsupervised feature extraction methods are principal component analysis [29], clustering based and random prototype selection [40]. In the research [22], it proposes unsupervised feature extraction based on dissimilarity space embedding of local neighborhoods around the points along the trajectory. Dissimilarity space embedding has high capability of discriminative representation and give benefit in classification process. Meanwhile, feature extraction is also performed in a supervised manner, where the target recognition task has a direct influence on the extraction process [29]. In [44], it introduces new method in feature extraction which is named as Hybrid Feature Extraction and Multiclass SVM based recognition method (HFE-MCSVM).

In the handwriting recognition system, there are many types of handwritten datasets. Some researchers develop their own datasets for the handwriting recognition by collecting the handwriting. Meanwhile, other researchers also use the data sets that provided online. In [8], it provided the first publicly available database name EMOTHAW (EMOTion recognition from HAndWriting and draWing) that link emotional states to handwriting and drawing. EMOTHAW contains surveys of 129 participants whose emotional states, including anxiety, depression, and tension are measured by the questionnaire of Depression – Anxiety – Tension Scales (DASS). The data sets use in [29] [20] are from Institut für Nachrichtentechnik/Ecole Nationale d'Ingénieurs de Tunis (IFN/ENIT) database. The database contains 32492 images of Tunisian city and village names written by hundred different writers. Moreover in [29], it also uses The RIMES database which contains more than 12000 mails written in French. The researcher utilized the 2009 variant of database which is partitioned into preparing, approval and test sets containing 44195, 7542 and 7464 pictures individually. [31] conducts an experiment using MYCT online signature datasets DB1 and the datasets DB2. The DB1 consists of 25 genuine and 25 skilled forgery samples of 100 writes. The DB2 consists of same number of genuine and forgery of 330 writers.

Other researchers also used handwritten digit images from The Chars74k database. The database is created by the compilation of photographs from the natural world and consists of 55 individual PNG images in each class from 0 to 9 [39]. Some research papers also used more than one data sets, as example, in [1] there are SET 1 and SET 2. SET 1 which tests the three properties of a segmented image containing an input object linked to the concavity, contour and character surface. SET 2 Is the MFEAT dataset composed of handwritten digits derived from the Dutch utility chart series. Datasets also have variety of language example Bangla, Hindi, Telugu and Arabic which are freely provided at www.code.google.com/cmaterdb [4]. For Chinese datasets, in [38] uses the HIT-MW Chinese database which is the first collection of Chinese handwritten text with 300 dpi resolution scanned handwriting. The datasets consist of 853 handwriting Chinese samples which 254 images from 241 writers are labelled by ID. Datasets for recognition system also have different pattern and type. For example, Isenkul at al's PD dataset containing the spiral drawing from 40 patient which are 25 Parkinson patients and 15 not Parkinson patients [45]. In [7], it uses Secure Password DB 150 and IAM online database. Secure Password DB150 contains of handwritten password that are collected from Spain and Germany and IAM online database contains of 1760 cursive text samples from 220 users.

3.3 RQ3: What are the techniques used in features ranking?

Features ranking is a very important step in recognition system. Features ranking goal is reducing the computational cost in classification process [1]. There are many techniques in features ranking. Ranking method are also known as filter method because it applied before the classification process to filter the less important variables [5]. Commonly used features ranking methods are Information Gain, Gain Ratio, Chi-Square, Symmetrical Uncertainty, Relief and Correlation [1] [4] [50]. The Chi-Square work with Chi-Square statistic to assess if the reciprocal frequency of

groups in neighboring intervals is sufficiently close to warrant a merger [1]. For the Relief, the algorithms work by sampling instances randomly from training data and function would earn a high weight if it differentiates between instances of different classes and provides the same meaning for instances of the same class [1]. Information Gain, Gain Ratio and Symmetrical Uncertainty are the concept of entropy. Information Gain measure the decrease of weighted averaged impurity of the partition, compared with the impurity of complete set of data [4]. There are disadvantages in Information Gain as it appears to favor properties with a higher number of potential values. Another method to solve this issue is to utilize the Gain Ratio, which penalizes multi-valued attributes. Symmetrical Uncertainty is another way to solve the issue of Information Gain prejudice against characteristics of more values by separating Information Gain by the sum of entropies of X and Y.

In the research of [6], it proposes a new approach for the features ranking in recognition system, incorporation of the concept of the value of the power of defining features and awareness of the relation between features. In order to classify the subset of the most appropriate features, the first best function can be identified by its powerful distinguishing power and placed in an empty collection of features. Alternatively, each of the remaining functionality is evaluated based on their effective efficiency capacity and the highest ranked attribute is added to the chosen subset. This cycle is replicated before the performance of the system hits its height or the positive meaning of the input drop below a certain level. Moreover, in another research such as [20], an accurate system of lexicon classification and reduction based on information on diacritical photos, amount of pieces of Arabic terms (PAWs) and measurements of information is used. Meanwhile in [49], each string of codes extracted from a character segment is fed to the HMM recognizer and the output is a ranked list of character labels with the associated HMM probabilities for one or more sequential segments. In order to avoid a computationally expensive exhaustive search and to be autonomous of a classification algorithm, a variety of heuristics are proposed to determine the consistency of the features as example ANOVA, Correlation, Joint-Entropy, Entropy-2Class and Entropy [21] [19]. To reduce the classification complexity, the size of database needs to reduce so that it can increase the classification accuracy.

In [43], it introduces a new ranking approach to minimize the size of the database by ordering the category groups from the nearest to the furthest, depending on the measured ranks. The approach starts with the estimation of simple regional-type features to tie together similar successful table classes utilizing decision trees. The purpose of this grouping method is to break the large database into multiple smaller ones. The study in [41] proposed filter-based feature selection method that focused on knowledge theory, feature rating and EC strategies for the quest of a collection of name-dominated solutions with a reduced number of features and equivalent or even stronger classification efficiency on the K-nearest neighbor algorithm than when all features. Researchers in [42] [26] proposed the hybridization of Grey Relational Analysis and Feature Subset Selection (GRAFeSS) as the features ranking method to determine the most significant subsets of features extracted from Higher-Order United Moment Invariant (HUMI) and Edge-based Directional (ED) feature extraction methods. Their proposed hybrid ranking method is able to yield the highest-ranking subsets of features that resulted to the best classification performance accuracy for writer identification of handwriting image.

3.4 RQ4: What are the strengths and weakness of the features ranking?

In the handwriting recognition, the large varieties in the handwriting of various authors resulted to difficulties in finding the collection of suitable features has been thoroughly studied. Features ranking is applied in handwriting recognition because the procedures for selecting an optimal subset of features can take a lot of time. [1]. Most recognition system implement features ranking technique because it has some significant advantages such as features ranking are independently applicable with any type of machines learning technique [17]. Moreover, features ranking is faster than feature selection techniques [34]. Other advantages states in [41] [36] is that features ranking methods are cheaper in computational cost compared to feature selection. In [52], features ranking is computationally and statistically scalable to large datasets and show good success for a variety of real-world application.

However, some of feature selection methods are found to be better than features ranking methods in some cases because the method takes into consideration of the classifier's hypothesis. This also means that, some feature selection methods can

handle feature dependencies compare to features ranking [34]. Both type of methods has their advantages and disadvantages

3.5 RQ5: What are the classifiers used in handwriting recognition?

The last important step in handwriting recognition is classification. In the classification step, it assigns the word to correct class label [27]. In the [30], used Convolutional Neural Network (CNN) and Support Vector Machine (SVM) for offline Arabic handwriting recognition. This model was found to automatically extract features from raw images and perform classification. There is also new method propose in classification. In the [47], it proposes an algebraic fusion of multiple classifiers trained on different sets. The result of the classification accuracy using the classifier fusion is more than 98%. Other researcher also proposes the combination of multiple classifiers to perform classification. The researcher in [35], performed multiple classifiers by aligning the output word sequence of each classifier using the Recognizer Output Voting Error Reduction (ROVER) and produce a good result of accuracies of 72.25% and 71.86%. For an Arabic handwritten word recognition, a multiple classifier system also has been proposed. In the paper [37], it uses multiple classifier system for Arabic handwritten word recognition. The first step is using Chebyshev moments (CM) enhanced with some Statistical and Contour-based Feature for describing word image. The next step for decision, the paper use multilayer perceptron (MLP), the support vector machine (SVM) and the Extreme Learning Machine (ELM) classifiers.

Meanwhile in other paper, SVM are widely chosen to be used in the classification task. In [33], it uses an open-source tool based on SVM which are call LIBSVM while in [28], it uses CNN trained for a larger class recognition problem towards feature extraction of sample of several smaller class recognition problem. In each case, a distinct Support Vector Machine (SVM) was used as the corresponding classifier. In [27], the classification is matching the selected class by the SVM with the character ASCII and find the desired word in Arabic lexicon. Finally, in [25], it proposed recognizing Assamese handwritten characters using HMMs and SVM stroke classifiers in conjunction to each other. The two classifiers are separately trained on same stroke dataset with same set of features.

6. LIMITATION

Features ranking is quick and independent of the classifier, but it overlooks feature interdependence and classifier interaction. They can also handle datasets with a lot of dimensions. As a result, feature selection only has to be done once, and different classifiers can then be compared. Features ranking have the problem of disregarding the interaction with the classifier and considering each feature individually, therefore neglecting feature relationships. Furthermore, it is unclear how to establish the ranking cutoff point to choose only the needed characteristics while excluding noise.

7. CONCLUSION

The aim of this systematic literature review is to study the features ranking methods, identify patterns and problems and record findings. Extensive search of complex keywords was conducted to check for primary studies utilizing five online databases. A total of 80 articles were obtained from the initial search. A collection of criteria was used against the initial search outcome and only 50 related papers were screened. A series of quality assurance requirements validated the eligibility of the 50 papers selected prior to this point. The in-depth review process collects the conclusions based on the researched questions.

A standard sequence of step in handwriting recognition were conceptualized in Figure 2. The systematic literature review found the general step in handwriting recognition first is feature extraction, second is features ranking and final is classification. Moreover, the systematic literature review discover that features ranking can overcome the problem of handwriting recognition such as computational cost. There are also many feature extraction methods in handwriting recognition. According to the systematic literature review, the use of more than one feature extraction method will extract more discriminative feature as much as possible. Various datasets are available for handwriting recognition. Datasets also available in many languages such as Bangla, Chinese and Arab.

The primary studies were grouped by features ranking method. The systematic literature review discovers many significant features ranking methods. The most used methods are Gain Ratio, Information Gain, Chi-Square, Symmetrical Uncertainty, Relief and Correlation. The methods were compared to feature selection to know their

weakness and strengths. It is a problem for systematic literature review to choose the best features ranking method for handwriting recognition. Therefore, instead of using one features ranking method, the future study would consider to fusion the features ranking methods to determine the significant feature of handwriting recognition.

8. FUTURE WORK

In future, the features ranking method is extremely crucial in constructing the ranking of each features that have been generated by features extraction process. The ranking process is aimed to produce their level of significance for each feature that allow the determination of the best features. The exploration of multiple ranking methods is important to establish their effectiveness and performance towards the handwriting images. Thus, in future, these ranking methods are aimed to be fusion to determine the best subsets of most significant features for handwriting recognition.

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REFERENCE

[1] Cilia, N. D., De Stefano, C., Fontanella, F., & di Freca, A. S. (2019). A ranking-based feature selection approach for handwritten character recognition. Pattern Recognition Letters, 121, 77-86.

[2] Gheyas, I. A., & Smith, L. S. (2010). Feature subset selection in large dimensionality domains. Pattern recognition, 43(1), 5-13.

[3] Singh, P., Verma, A., & Chaudhari, N. S. (2015). Feature selection based classifier combination approach for handwritten Devanagari numeral recognition. Sadhana, 40(6), 1701-1714.

[4] Roy, A., Das, N., Saha, A., Sarkar, R., Basu, S., Kundu, M., & Nasipuri, M. (2015). A comparative study of feature ranking methods in recognition of handwritten numerals. In Artificial Intelligence and Evolutionary Algorithms in Engineering Systems (pp. 473-479). Springer, New Delhi.

[5] Chandrashekar, G., & Sahin, F. (2014). A survey on feature selection methods. Computers & Electrical Engineering, 40(1), 16-28.

[6] Kang, S., & Govindaraju, V. (2005, August). A new feature ranking method in a HMM-based handwriting recognition system. In Eighth International Conference on Document Analysis and Recognition (ICDAR'05) (pp. 779-783). IEEE.

[7] Kutzner, T., Pazmiño-Zapatier, C. F., Gebhard, M., Bönninger, I., Plath, W. D., & Travieso, C. M. (2019). Writer identification using handwritten cursive texts and single character words. Electronics, 8(4), 391.

[8] Likforman-Sulem, L., Esposito, A., Faundez-Zanuy, M., Clémençon, S., & Cordasco, G. (2017). EMOTHAW: A novel database for emotional state recognition from handwriting and drawing. IEEE Transactions on Human-Machine Systems, 47(2), 273-284.

[9] Liwicki, M., & Bunke, H. (2007, January). Feature selection for on-line handwriting recognition of whiteboard notes. In Proc. Conf. of the Graphonomics Society (pp. 101-105).

[10] He, Z., You, X., & Tang, Y. Y. (2008). Writer identification using global wavelet-based features. Neurocomputing, 71(10-12), 1832-1841.

[11] Fernandez-de-Sevilla, R., Alonso-Fernandez, F., Fierrez, J., & Ortega-Garcia, J. (2010, November). Forensic writer identification using allographic features. In 2010 12th International Conference on Frontiers in Handwriting Recognition (pp. 308-313). IEEE.

[12] Hassan, E., Chaudhury, S., & Gopal, M. (2010, November). Identity determination with offline handwritten input using multi kernel feature combination. In 2010 12th International Conference on Frontiers in

Handwriting Recognition (pp. 84-88). IEEE.

[13] Hassan, E., Chaudhury, S., & Gopal, M. (2010, November). Identity determination with offline handwritten input using multi kernel feature combination. In 2010 12th International Conference on Frontiers in Handwriting Recognition (pp. 84-88). IEEE.

[14] Kitchenham, B., Brereton, O. P., Budgen, D., Turner, M., Bailey, J., & Linkman, S. (2009). Systematic literature reviews in software engineering–a systematic literature review. Information and software technology, 51(1), 7-15.

[15] Galster, M., Weyns, D., Tofan, D., Michalik, B., & Avgeriou, P. (2013). Variability in software systems—a systematic literature review. IEEE Transactions on Software Engineering, 40(3), 282-306.

[16] Anu, V., Hu, W., Carver, J. C., Walia, G. S., & Bradshaw, G. (2018). Development of a human error taxonomy for software requirements: a systematic literature review. Information and Software Technology, 103, 112-124..

[17] Poovizhi, P. (2014). A study on preprocessing techniques for the character recognition. International Journal of Open Information Technologies, 2(12).

[18] Ghanim, T. M., Khalil, M. I., & Abbas, H. M. (2018, September). Phog features and kullback-leibler divergence based ranking method for handwriting recognition. In IAPR Workshop on Artificial Neural Networks in Pattern Recognition (pp. 293-305). Springer, Cham.

[19] Choudhury, H., & Prasanna, S. M. (2019). Representation of online handwriting using multi-component sinusoidal model. Pattern Recognition, 91, 200-215..

[20] Ahlawat, S., & Rishi, R. (2018, September). Handwritten digit recognition using adaptive neuro-fuzzy system and ranked features. In 2018 International Conference on Computing, Power and Communication Technologies (GUCON) (pp. 1128-1132). IEEE.

[21] Chherawala, Y., Roy, P. P., & Cheriet, M. (2015). Feature set evaluation for offline handwriting recognition systems: application to the recurrent neural network model. IEEE transactions on cybernetics, 46(12), 2825-2836.

[22] Khorsheed, M. S., & Clocksin, W. F. (1999, September). Structural Features of Cursive Arabic Script. In BMVC (pp. 1-10).

[23] Arica, N., & Yarman-Vural, F. T. (2002). Optical character recognition for cursive handwriting. IEEE transactions on pattern analysis and machine intelligence, 24(6), 801-813.

[24] Lawgali, A., Bouridane, A., Angelova, M., & Ghassemlooy, Z. (2011). Handwritten Arabic character recognition: Which feature extraction method?. International Journal of Advanced Science and Technology, 34, 1-8..

[25] Novaković, J. (2016). Toward optimal feature selection using ranking methods and classification algorithms. Yugoslav Journal of Operations Research, 21(1).

[26] Shabbir, A., Javed, K., Babri, H. A., & Ansari, Y. (2016). Stability of Feature Ranking Algorithms on Binary Data. Pakistan Journal of Engineering and Applied Sciences.

[27] Lorigo, L. M., & Govindaraju, V. (2006). Offline Arabic handwriting recognition: a survey. IEEE transactions on pattern analysis and machine intelligence, 28(5), 712-724.

[28] Elleuch, M., Maalej, R., & Kherallah, M. (2016). A new design based-SVM of the CNN classifier architecture with dropout for offline Arabic handwritten recognition. Procedia Computer Science, 80, 1712-1723.

[29] Ooi, S. Y., Teoh, A. B. J., Pang, Y. H., & Hiew, B. Y. (2016). Image-based handwritten signature verification using hybrid methods of discrete radon transform, principal component analysis and probabilistic neural network. Applied Soft Computing, 40, 274-282.

[30] Bhattacharya, N., Roy, P. P., Pal, U., & Setua, S. K. (2018). Online Bangla handwritten word recognition. Malaysian Journal of Computer Science, 31(4), 300-310.

[31] Frinken, V., Bhattacharya, N., & Pal, U. (2014, April). Design of unsupervised feature extraction system for on-line Bangla handwriting recognition. In 2014 11th

IAPR International Workshop on Document Analysis Systems (pp. 355-359). IEEE.

[32] Frinken, V., Bhattacharya, N., & Pal, U. (2014, April). Design of unsupervised feature extraction system for on-line Bangla handwriting recognition. In 2014 11th IAPR International Workshop on Document Analysis Systems (pp. 355-359). IEEE.

[33] Eraqi, H. M., & Abdelazeem, S. (2012, September). HMM-based offline Arabic handwriting recognition: Using new feature extraction and lexicon ranking techniques. In 2012 International Conference on Frontiers in Handwriting Recognition (pp. 554-559). IEEE..

[34] Manjunatha, K. S., Manjunath, S., Guru, D. S., & Somashekara, M. T. (2016). Online signature verification based on writer dependent features and classifiers. Pattern Recognition Letters, 80, 129-136.

[35] Tan, G. J., Sulong, G., & Rahim, M. S. M. (2017). Offline Text-Independent Chinese Writer Identification Using GLDM Features. Journal of Telecommunication, Electronic and Computer Engineering (JTEC), 9(3-3), 177-184.

[36] Poon, C., Gorji, N., Latt, M., Tsoi, K., Choi, B., Loy, C., & Poon, S. (2019, January). Derivation and analysis of dynamic handwriting features as clinical markers of parkinson's disease. In Proceedings of the 52nd Hawaii International Conference on System Sciences.

[37] Makrushin, A., Scheidat, T., & Vielhauer, C. (2011, July). Towards robust biohash generation for dynamic handwriting using feature selection. In 2011 17th International Conference on Digital Signal Processing (DSP) (pp. 1-6). IEEE.

[38] Makrushin, A., Scheidat, T., & Vielhauer, C. (2012). Improving reliability of biometric hash generation through the selection of dynamic handwriting features. In Transactions on data hiding and multimedia security VIII (pp. 19-41). Springer, Berlin, Heidelberg.

[39] Hancer, E., Xue, B., & Zhang, M. (2018). Differential evolution for filter feature selection based on information theory and feature ranking. Knowledge-Based Systems, 140, 103-119.

[40] Jalil, I. E. A., Shamsuddin, S. M., Muda, A. K., Azmi, M. S., & Hashim, U. R. A. (2018). Predictive based hybrid ranker to yield significant features in writer identification. International Journal of Advances in Soft Computing & Its Applications, 10(1).

[41] Jalil, I. E. A., Muda, A. K., Shamsuddin, S. M., & Ralescu, A. (2013, December). Geometrical feature based ranking using grey relational analysis (GRA) for writer identification. In 2013 International Conference on Soft Computing and Pattern Recognition (SoCPaR) (pp. 152-157). IEEE.

[42] Liu, H., Motoda, H., Setiono, R., & Zhao, Z. (2010, May). Feature selection: An ever evolving frontier in data mining. In Feature selection in data mining (pp. 4-13). PMLR.

[43] Suto, J., Oniga, S., & Sitar, P. P. (2016, May). Comparison of wrapper and filter feature selection algorithms on human activity recognition. In 2016 6th International Conference on Computers Communications and Control (ICCCC) (pp. 124-129). IEEE.

[44] Suto, J., Oniga, S., & Sitar, P. P. (2016). Feature analysis to human activity recognition. International Journal of Computers Communications & Control, 12(1), 116-130.

[45] Yan, W. (2007, July). Fusion in multi-criterion feature ranking. In 2007 10th international conference on information fusion (pp. 1-6). IEEE.

[46] Kadhm, M. S., & Hassan, A. K. A. (2015). Handwriting word recognition based on SVM classifier. International Journal of Advanced Computer Science & Applications, 1(6), 64-68.

[47] Zhao, H. H., & Liu, H. (2020). Multiple classifiers fusion and CNN feature extraction for handwritten digits recognition. Granular Computing, 5(3), 411-418.

[48] Kumar, P., Saini, R., Roy, P. P., & Pal, U. (2018). A lexicon-free approach for 3D handwriting recognition using classifier combination. Pattern Recognition Letters, 103, 1-7.

[49] Tamen, Z., Drias, H., & Boughaci, D. (2017). An efficient multiple classifier system for Arabic handwritten words

recognition. Pattern Recognition Letters, 93, 123-132.

[50] Sarkhel, R., Das, N., Saha, A. K., & Nasipuri, M. (2016). A multi-objective approach towards cost effective isolated handwritten Bangla character and digit recognition. Pattern Recognition, 58, 172-189.

[51] Maitra, D. S., Bhattacharya, U., & Parui, S. K. (2015, August). CNN based common approach to handwritten character recognition of multiple scripts. In 2015 13th International Conference on Document Analysis and Recognition (ICDAR) (pp. 1021-1025). IEEE.

[52] Choudhury, H., Mandal, S., Devnath, S., Prasanna, S. M., & Sundaram, S. (2015, December). Combining HMM and SVM based stroke classifiers for online Assamese handwritten character recognition. In 2015 Annual IEEE India Conference (INDICON) (pp. 1-6). IEEE.

[53] L. Cordella , C. De Stefano , F. Fontanella , C. Marrocco , A feature selection algorithm for handwritten character recognition, in: 19th International Conference on Pattern Recognition (ICPR 2008), 2008, pp. 128–131 .

[54] C.M. Nunes , A.d.S. Britto Jr. , C.A .A . Kaestner , R. Sabourin , An optimized hill climbing algorithm for feature subset selection: evaluation on handwritten character recognition, in: Proceedings of the 9-th Int. Workshop on Frontiers in Handwriting Recognition (IWFHR'04), IEEE Computer Society, Washington, DC, USA, 2004, pp. 365–370 .