A DEEP STUDY ON EPSO-EKNN ALGORITHM AS COMPARED TO DBN ALGORITHM

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Abstract

Offline character recognition has become a highly important study field for various pattern recognition applications in recent years. Several handwritten character recognition systems have been suggested, with the complexity of these systems varying depending on the recognizing units' writing styles. In reality, identifying letters or numerals is far simpler than recognizing cursive sentences or lines of text. As a result, early handwriting recognition algorithms could only distinguish a few characters with limited vocabularies. Nowadays Arabic handwritten character recognition is very important as it is very difficult to identify. The cursive writing and variety of styles make this recognition more complex.

This paper presents an automated model for ACR. This ACR is constructed from four phases: Preprocessing, Segmentation, Feature Extraction, and Classification. In this research article, We compare the advanced EPSO EKNN Algorithm with the earlier DBN Algorithm and also suggest a new method having higher Accuracy.

In this research article, the "Enhanced K-Nearest Neighbor" (EKNN) classification model was used to identify and classify or simply recognize the particular Arabic character, and the "Extended Particle Swarm Optimization" (EPSO) methodology was introduced to select the best feature from feature extraction to comply with Arabic-Character Classification. As compared to Deep belief networks, the developed EPSO –EKNN Algorithm has higher accuracy.

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I INTRODUCTION

Arabic handwritten character recognition is more complex as compared to other languages due to its shape, position, Overlapping etc.

Many scientists have been drawn to this CR because of the large collection of publications found on the website, in a mailbox, and in academic resources, as well as its primary use in several basic practical systems such as narratives classified by subjects, scholarly articles, and online sources in library collections, which are typically organized by professional areas and subdirectories, including spam detection, which categorizes email.[1] Automation of CR is critical for saving money and time while increasing recognition accuracy. Both the CR and traditional classifying challenges need data preparation to continue increasing the classifier's performance.[2]

OCR research has progressed a long way since its humble beginnings. Since, OCR research has gained a lot of traction and absorbed a lot of knowledge. Several significant surveys have been discovered. In journals and conference proceedings, a large number of related articles have been published. Several books on the subject have been released. Document processing systems got more robust and precise as faster processing and larger storage became more widely available and inexpensive. Automatic extraction of meaningful data from multiple online data sources in many languages is gaining pace.[3]

The process of turning the spatial representation of text, such as a scanned document, into its symbolic representation, such as ASCII characters, is known as optical character recognition (OCR). It is assumed that handwritten text will be recognized by an automated system.[4][5]This is beneficial in a variety of new applications that are continually being developed. It may be used to process scanned documents, obtain data/commands from hand-held devices, verify writers' identities, and so on. In figure 1.1 it shows the Arabic characters.

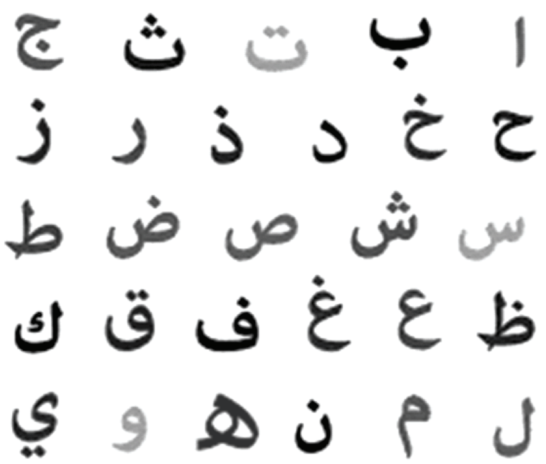

Fig 1.1 : Arabic Characters

More than 250 million people speak Arabic as their first language. It is the third most widely used worldwide language, with approximately one billion Muslims using it in their various religious activities. There are other languages that employ the Arabic script in addition to Arabic, including Urdu, Farsi (Persian), Pashto, Jawi, and Kurdish. Although a conclusion may summarise the key points of the Arabic text, In both machine printed and handwritten scripts, it is commonly written in cursive and from right to left. Each of the 28 fundamental letters of the Arabic alphabet is made up of dots and symbols. The no. of dots placed above and below the characters differentiate it. It also depends on the no of dots. Each character in Arabic has different shapes based upon the position like the beginning, middle and end. Six of the 28 basic Arabic letters can only be linked from one direction, whereas the remaining 22 may be joined from both directions. These six characters are Alef (ا)(Dal (د) , (Thal , (Thal ,(ذ) Ra (ر ,)Zy (ز ,)and Waw (و)[6][7]

II LITERATURE SURVEY

A hybrid FS technique was developed by the researchers of [8] to increase the accuracy of the clusters in the websites. The term frequency, inverse document frequency, CHI2, and mutual information are included in this new FS method. According to some journals, some researchers introduced k mean's clustering technique and increased the quality up to 28 percentage.

Azuraliza, A.B., Siti Rohaidah, A., Nurhafizah Moziyana, M.Y., and Yaakub, M.R. (ACO).introduced a unique Feature selection method for sentimental analysis based on anti-colony-optimization. And they also optimized the effectiveness of this technique using a KNN classifier and some datasets from the customer as feedback[9].

They also compare the results using the factors like Information gain. Genetic algorithm and Rough set Attribute reduction. The researchers achieved an enhanced accuracy of 0.914.

The researchers published an Alphanumeric extremely DeepNeural-Network in [10] Mudhsh MA, Almodfer R (2017) provided a solution for the identification of Handwritten Arabic digits and characters. A classification model was built using 13 convolutional layers, 2 max-pooling layers, and 3 totally connected layers. Two normalizing approaches, Augmentation and Dropout, were utilized to minimize the number of parameters. The AD-Base dataset (a collection of Handwritten Arabic values from 0-9) and the HACDB dataset were used in the testing (a dataset of Characters with Arabic Handwritten). The ADBase dataset has a 99.67 percent accuracy rate, whereas the HACDB dataset has a 97.42 percent accuracy rate.

Younis K (2018) developed a CNN to recognize Arabic handwritten letters in[11]. In their proposed CNN, three convolutional layers were offered, along with totally linked layers. Testing results demonstrated that the CNN could achieve 94.8 percent and 94.9 percent accuracy, respectively, utilizing the AHCD and AIA9K datasets. Peng, C., Limc, S., Chin Neoh, L., Zhang, K., Mistry, K., (2018)[12] built a hybrid-based FS by integrating this with Simulated-Annealing to improve the findings. They used 11 regressions and 29 classification datasets to test the novel method and compare it to existing methods. These are all favorable results.

III DEEP BELIEF NEURAL NETWORKS

Generally, deep belief networks have several hidden variables and one visible layer of units.

It may be trained with efficient greedy training with each layer as an RBM. By using DBN we can learn one layer of the hidden feature at a time

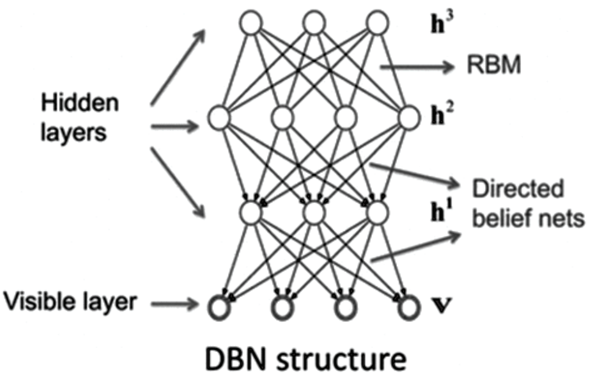

Fig : 3.1 A DBN with 3 Hidden layers

3.1 Restricted Boltzmann Machines

The Restricted Boltzmann Machines (RBM) is a probabilistic generative model with visible units v and hidden units h. The visible and concealed units are linked by the weight matrix W. There are no connections between the strata's units. The energy function of an RBM and its probabilistic semantics are as follows:

$$E(v,h;\theta) = -\sum_{i=1}^{V}\sum_{j=1}^{H} w_{ij} v_i h_j - \sum_{i=1}^{V} b_i v_i - \sum_{j=1}^{H} a_j h_j \quad (1)$$

$$p(v;\theta) = \frac{1}{Z}\sum_{h} e^{-E(v,h;\theta)} \quad (2)$$

Where wij represents the weights of visible units vi and hidden units hj, bi and aj represent their biases, and = (W, b, a) represents the weights of visible units vi and hidden units hj. The partition function is represented by the letter Z. V and H stand for visible and hidden units, respectively.[13] The probability of hidden unit hj being activated given visible vector v and the likelihood of visible unit vi being activated given hidden vector h are given by for binary (or real valued) visible and hidden units.

$$P(h_j|v;\theta) = \sigma\left(a_j + \sum_i w_{ij} v_i\right) \quad (3)$$

$$P(v_i|h;\theta) = \sigma\left(b_i + \sum_j w_{ij} h_j\right) \quad (4)$$

The logistic sigmoid is denoted by. For the activation function, this logistic function (x)=1/1+e-x is a popular choice

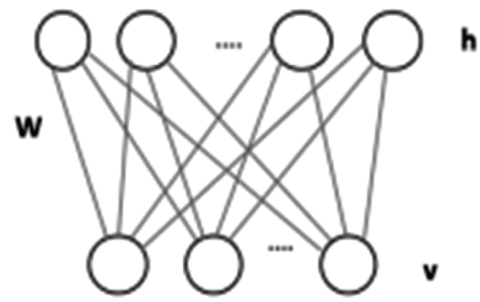

Fig: 3.2 Restricted Boltzmann Machine and Parameters

IV EPSO-EKNN METHOD

The key modules of the developed AOCR mechanism are highlighted in Figure 3. EPSO is used to find the most useful characteristics, while EKNN-Classifier is used to recognize Arabic characters in each class. Training and testing are the two steps of the mechanism. There are several steps to the AOCR mechanism technique. The bulk of these steps are seen in nearly all OCR methods. In this study, the two steps of feature selection and classification are explored in depth.

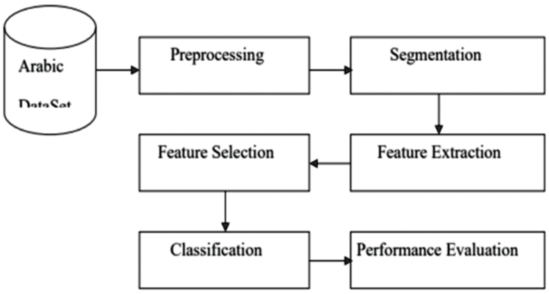

Fig: 4.1 Basic OCR Steps

Despite the availability of several standard Arabic datasets, the recommended model relies on the best printable datasets with good quality, a range of dimensions, and font kinds. The "APTI" dataset was studied, which comprises 113,285 textual images, 12 Arabic fonts, 11 font sizes, and 5 font styles. With different sample changes, the size, font styles, alignment, and noise level

4.1 Pre-processing

Pre-processing is a standard requirement in terms of improving the accuracy of classification. To create normalized and centralized character images, pre-processing processes have been used. OCR performance is significantly improved by this pre-processing. The preceding procedures were used for pre-processing in this research

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(i) Normalization of Sizes: After getting the character image from the dataset as an input. The image must be normalized and consolidated in an attempt to obtain the highest recognition accuracy. The image dimension is resized to a set dimension by normalizing. Most of the images in this category have been scaled down to 64 by 64 pixels and transformed to grayscale coloring maps.

(ii) Centralizing: Characters appeared in numerous orientations in many of the images (left, right, bottom and top). To begin, the character's and image's centroid are computed independently in an attempt to align all of the characters around the same place and compute correct characteristics for each Arabic-characters. Because the character is 64 by 64 dimensions in scale, the character's center point is 32 by 32 in this scenario. The character's centroid is therefore moved to the image's centroid to create a centered image. As illustrated in Figure 4, every sample's image goes through 5 procedures to qualify for segments. The above activities include: (a) converting the images into grayscale and also to binary sequence, (b) attempting to remove noisy data from images using an appropriate Median-Filter, (c) attempting to remove all tiny artifacts using morphology operation of close and open, (d) rotating the image, and (e) reformatting the image to applicable measurements to manage the dimension issue because a few of the characters seem to be smaller.

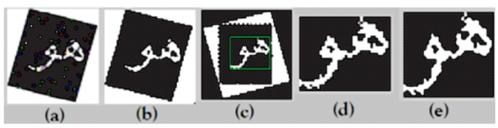

Fig: 4.2 Preprocessing Process

4.2 Segmentation

Given that text segmentation appears to be a key factor in detecting issues, the proposed method foregoes these steps in favour of pre-segmentation (words free segmentation). On the other hand, because the images in the dataset are lines of text, they will be divided individually. In this study, a Line-Segmenting approach was utilised to identify and segregate distinct textual lines from a computerised picture text for post-processing feature extraction. In order to separate the characters using this LineSegmenting method, the following challenges must be overcome: I Overlapping line boundaries; (ii) Lines that touch; (iii) Shattered lines; (iv) Absence of fundamental data; Inside the lines: (v) Curved letter, (vi) Piecewise straight letter, (vii) Connecting letters and phrases.

V FEATURE EXTRACTION

Following segmenting, the extraction of features stage's primary objective is to maximize detection performance with the fewest amount of features contained in a vector space. The objective of this process is to extract different various features from the character segmented image which have a significant level of resemblance between sampling of the respective classes and a significant level of variance between samples of different classes. Second-order fact based techniques outperformed power spectral density (transformation) and structuring approaches in terms of differentiating levels. Image intervals delivered the greatest outcomes from such second-order facts. As a result, the suggested framework uses a collection of 14 features From GLCM (Gray level Co-occurrence matrix) seems to be scale-invariant and hence reliant on invariance moments.

The first-order facts of a character image, which are focused on specific pixel features and are derived from Standard-Deviation and Mean. GLCM, essentially accounted for the spatially interrelationship or co-occurrence of 2 pixels at certain relative locations, may be used to derive an image's second-order facts. The fourteen features of Difference-Entropy, Difference-Variance Angular-Second-Moment, Correlations, Contrasting, Sum of Squares or Variance, Inverse-Difference-Moment, Sum-Average, Sum-Entropy, Sum-Variance, , Information-Measure of Correlations and Cluster-Tendency have been determined for the orientations of each matrix. Homogeneity, Entropies, Contrasting, and Energies are all impacted by the orientation chosen. Upon that foundation of the frequencies, the Entropies and Homogeneity provide an indicator of the dominant values of the major diagonal. The energy provides information about the geographical distribution's unpredictability.

The co-occurrence matrices computations have the benefit of allowing co-occurring pairings of pixels to be spatially linked in a multitude of orientations in terms of distance and angular spatial connections, rather than only two pixels at a time. As a result, it seems that the mix of grey levels and their locations will be seen there. The outcome among those feature vectors would then be used in the feature selection procedure.

5.1 Feature Selection (EPSO)

(i) Particle Swarm Optimization (PSO)

Eberhart and Kennedy invented PSO in 1995 which was a population related stochastic method. A population with particles has been used to initialize the PSO. Every particle has been seen as a single point inside an "S" dimensional environment. "$X_i = (x_{i1}, x_{i2},..., x_{iS})$" represents the "$i^{th}$" particle. Any particle's previous best position is "p_{best}" (higher value of fitness) was "$P_i = (p_{i1}, p_{i2},..., p_{iS})$". The "$g_{best}$" is the index of the best global particle. The "$V_i = (v_{i1}, v_{i2},..., v_{iS})$" is the particle's velocity of 'i'. These particles are computed using the equations below:

$$v_{id} = w^* v_{id} + c1^* rand()^*(p_{id} - x_{id}) + c2^* Rand()^*(p_{ad} - x_{id}) \quad \text{Eq (1)}$$

$$x_{id} = x_{id} + v_{id} \quad \text{Eq (2)}$$

Here 'w' has been the weight of inertia. The weighting of the stochastic accelerating factors which drive every particle nearer "pbest" and "gbest" locations is represented by the accelerated constants "c1" and "c2" in Equation (1). This Basic PSO was designed to solve issues involving continual optimizing. The basic PSO idea must be modified to cope with binary information in need to conduct better FS. The Fitness-Function 'f' will be a discrete-function, and the search-space 'D' could be a limited collection of states. The literature proposes many variants of binary and discrete based PSO.

(ii) Extended PSO (EPSO) for Feature Selection:

For binary-bit strings, the particle's location is expressed as "N" length, where "N" indicates the whole range of characteristics. Each bit represents an attribute; a value of '1' indicates that the corresponding attribute is selected, whereas a value of '0' indicates that it is not. Every location is a subset of an attribute in this system. Following the calculation of velocities and positions using Equations (1) and (2), it applies a sigmoid transformation to the velocity component using Equation (3), compressing velocities with ranges of [0, 1].

$$S(v_{id}^{new}) = \frac{1}{1+e^{-v_{id}^{new}}}$$
$$\text{if } (rand < S(v_{id}^{new})) \text{ then } x_{id}^{new} = 1; \qquad \text{Eq (3)}$$
$$\text{else } x_{id}^{new} = 0$$

Hereby "xidnew" has been the current-value of the "i" individual in the "d" dimension and "vidnew" has been the current velocity of the "i" individual in the "d" dimension.

Fitness-Function: The accompanying fitness function has been used in this research.

$$Fitness = \alpha * \gamma(F_i(t)) + \beta * \frac{|N| - |F|}{|N|} \qquad \text{Eq (4)}$$

Whereas "$F_i(t)$" is the subset of features discovered by particle 'i' of 't' iteration, "γ(Fi(t))" has been the quality of the classification for the selected features, the |F| has been the length of the subset of the features selected. The entire feature number is represented by |N|. With each iteration of this process, the inertia weight lowers in this method. The size of the swarm had been setted as 30 and the coefficient weight had been setted as 1.2 initially and 0.4 in the final. The accelerating positive constants 'C1' and 'C2' had been setted to 2. Figure 5 depicts the schematic of the proposed FS algorithm.

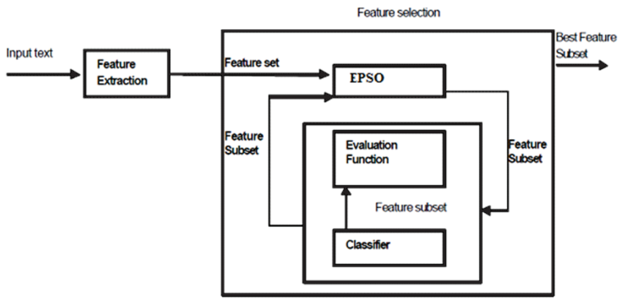

Fig: 5.1 Proposed FS Schematic Diagram

The EPSO mechanism is implemented in the following way:

- Create a particle's population having randomized position and randomized velocities in the feature-space on 'S' dimensions. "Pi" should be initialized with copies of "Xi", and "Pg"should be initialized with the index of the particle in the population with the greatest fitness-function value.

- Evaluate the required optimization fitness-function as by Equation (4) in 'd' variables for every particle.

- If the current value is better than the “pbest” then the “Pbest” is set to the current value in ‘d’ dimensional space.

- Compare th fitness assessment of the population and if the current value is better than the “gbest” then the "gbest" value is reset to the current value.

- Equations (1) and (2) should be used to adjust the particle's velocities and positions.

- Loop will continuous until the criteria is satisfied.This is the best level of fitness or a maximum frequency of iterations.

- The Arabic text is represented using a vector space representation, and the weight is determined using the Equation below.

$$w_{kj} = \frac{tf \times idf(t_k, d_j)}{maxtf} \quad \text{Eq (5)}$$

- w_{kj} is the weight of the character k of document j
- tf is the term frequency
- idf is the inverse document frequency

Experimental configuration for FS based on EPSO:

The following are the key stages in the EPSO based FS simulation:

- We've divided the data into 10 groups. In the Arabic-Dataset, each group includes training and testing documents for each category. With a ten percent increase, it had been included negative examples from different categories to each group for both training and testing documents.

- Each group's documents have been preprocessed.

- Then, for each group, the EPSO based FS methodology is utilized to the entire feature space to choose the optimal FS subset that best represents the FS space.

- According to the defined learning method, the optimized FS subset was deployed to a classification algorithm to execute the categorization job (binary classifying).

VI CLASSIFICATION (EKNN)

6.1 KNN

The KNN is being a supervised technique of learning which is one of the simplistic of Machine-Learning methods. The technique uses the closest k-samples from training-sets to classify an unknown sample-class. KNN originally stood for "nearest k samples", which may be found by the distance calculation. The unknown-category is the one with the highest numbers in class.

In figure 6 the left side shows 3 samples as "square", "Circle", and "Triangle" and an unknown "Rhombus". Each no represents the distance order.1 means the closest and 4 means the longest distance.

Class A has a higher probability as in figure 6 so the unknown sample assigned to class A

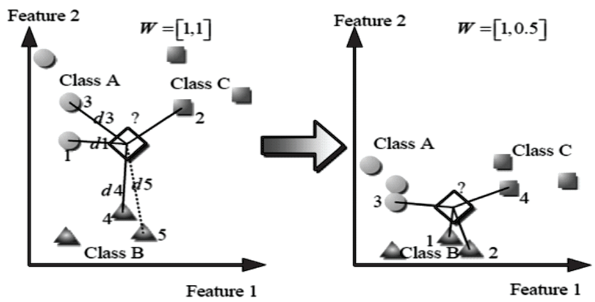

Figure 6.1: Schematic of Enhanced-KNN (EKNN) Classification

To demonstrate the similarity, K-NN uses a distance metric, typically Euclidean-Distance (ED). If " X = (x1, x2,..., xn) and Y = (y1, y2,..., yn)" are n-dimensional vectors, then the ED computes as follows:

$$dist(X,Y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_n - y_n)^2} \quad \text{Eq (6)}$$

Even so, K-NN has the following shortcomings:

- The weights of all features were equivalent. The positive-correlation does not exist for all features of the categorized outcomes. The error categorized outcomes are due to improper features.

- In this case, an identical probability will arise. If the nearest neighbor is included then the probability of Class A, B, and C is 40%,40%, and 20% respectively. Class A and B has same probability.

- **(ii) Enhanced-KNN (EKNN)**

The classification outcome of KNN was sensitive to features, which is a KNN drawback. The performance of the classifier is lowered by improper features. The EKNN is used to add weights to overcome this disadvantage. Numerous weights were employed for various features. The weight "W = [w_1,w_2,..., wn]" is used to calculate the weighted distance in "x" as described in the following:

$$dist(X,Y) = \sqrt{w_1(x_1-y_1)^2 + w_2(x_2-y_2)^2 + \cdots + w_n(x_n-y_n)^2} \quad \text{Eq (7)}$$

I n the above figure 6 the weight of the left side is "W = [1, 1]" and the weight on right side is "W = [1, 0.5]". Equation 7 will shows how the weight changes may affect the result.

Since Class-A has a higher probability at first, once the weight is adjusted, Class-B will have a higher probability than Class-A. Feature 2 has a much less impact on classifying outcomes. To improve the accuracy of classification, the weight adjustments may change the impact of various features on the recognition rate and remove some incorrect features.

This research study proposes the distance calculation to classify the KNN outcome that produces equal probability. Here Class A and class b have equal probability. here it calculates the distance between class A and class B and each of their two test points. The distance between the KNN test points and class A is d1 and d3. The distance between KNN test points and class B is d4 and d5.then the total of the smaller distances to the class is the decision outcome.

$$\begin{cases} D = \text{Class A if } d1 + d3 < d4 + d5 \\ D = \text{Class B if } d1 + d3 > d4 + d5 \end{cases} \quad \text{Eq (8)}$$

This technique will helps to reduce the same probability problem and improve the accuracy. The EKNN is a updated classification of KNN by a weighted KNN based on EPSO data from fearure selection. With Leave-One-Out-Cross-Validation "LOOCV", This EPSO optimizes the weights and evaluate the prediction classification accuracy of EKNN. The total of recognized accuracy is calculated as Predictive-Classification-Accuracy "pcaCV" for all classes.

$$pca_{CV} = \frac{N_{Correctly}}{N_{Total}} \times 100\% \quad \text{Eq (9)}$$

VII RESULTS AND DISCUSSIONS

A significant number of tests have been conducted to assess the proposed EPSO-EKNN method. This section includes the comparative results between the DBN and EPSO-EKNN in an attempt to evaluate the effectiveness of this research work. Here it utilized the APTI-Arabic databases for this recognizing the Arabic characters. For the classification work, the code was written and developed in the Matlab2016 platform.

(i) Accuracy

The confusion-matrix between both the actual information and also the character recognition (CR) output is used to measure accuracy. The following formula should be used to determine accuracy:

"**Accuracy** = (True-Negative + True-Positive) / (True-Negative + True-Positive + False-Negative + False-Positive)"

Arabic-Datasets	DBN	EPSO-EKNN
ArabicImage-1	89.5	94.5
ArabicImage-2	90.5	95.5
ArabicImage-3	89.5	94.5
ArabicImage-4	88.5	93.5
ArabicImage-5	87.5	92.5

Table 7.1: Numerical Accuracy Comparison

Arabic-Datasets	DBN	EPSO-EKNN
ArabicImage-1	90	95
ArabicImage-2	91	96
ArabicImage-3	90	95
ArabicImage-4	89	94
ArabicImage-5	88	93

Table 7.2: Numerical Precision Comparison

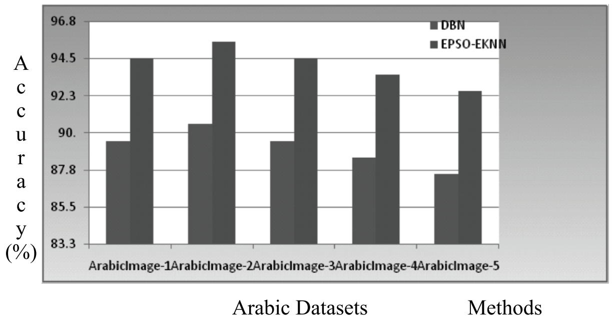

Fig 7.1: Graphical Accuracy Comparison

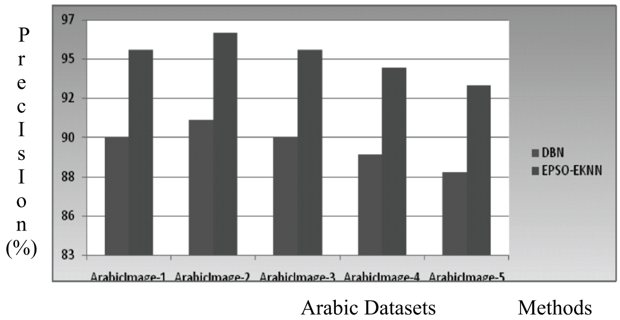

Fig 7.2: Graphical Precision Comparison

This procedure is carried out on all images in the datasets. The findings are produced after evaluation upon CR utilizing actual reality information. Table 1 and Figure 7 shows the maximum accuracy of the CR was lower without selecting optimal features for AOCR by DBN and higher for following optimal feature selection by EPSO for AOCR by EPSO-EKNN.

(ii) Precision

The Precision refers to the ratio of the number of character recognition in the particular image that was correctly assigned in that respective category class to the total number of images classified as belonging to respective categories.

"**Precision** = (True-Positive) / (True-Positive + False-Negative)"

This procedure is carried out on all images in the datasets. The findings are produced after evaluation upon CR utilizing actual reality information. Table 2 and Figure 8 shows the maximum precision of the CR was lower without selecting optimal features for AOCR by DBN and higher for following optimal feature selection by EPSO for AOCR by EPSO-EKNN.

(iii) Recall

Recall refers to the ratio of the number of characters correctly assigned in the respective category to the total number of images belonging to that particular category in original datasets.

"**Recall** = (True-Positive) / (True-Positive + False-Positive)"

Arabic-Datasets	DBN	EPSO-EKNN
ArabicImage-1	91.5	96.5
ArabicImage-2	92.5	97.5
ArabicImage-3	91.5	96.5
ArabicImage-4	90.5	95.5
ArabicImage-5	89.5	94.5

Table 7.3: Numerical Recall Comparison

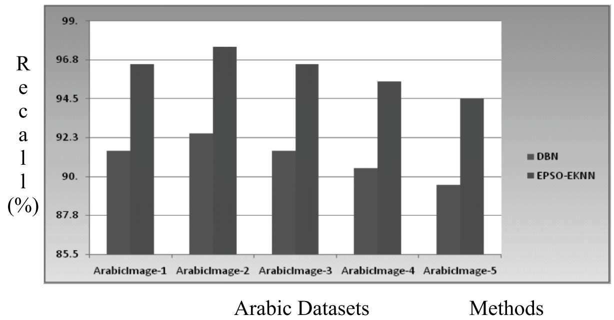

Fig. 7.3: Graphical Recall Comparison

This procedure is carried out on all images in the datasets. The findings are produced after evaluation upon CR utilizing actual reality information. Table 3 and Figure 9 show the maximum recall rate of the CR was lower without selecting optimal features for AOCR by DBN and higher for following optimal feature selection by EPSO for AOCR by EPSO-EKNN.

VIII CONCLUSION

The CR is likely the most challenging stage in the OCR research process. Over the last few decades, cursive-character recognition has gotten a lot of attention in academia. On the other hand, the lack of a consistent dataset makes it extremely challenging. To address these challenges, this article provides an OCR approach for Arabic characters. In this research, we provide an upgraded version of standard PSO (EKNN) classifier for AOCR Classification and an expanded version of standard PSO (EPSO) for FS, both of which were evaluated on the Arabic-Dataset. The Inertia-Parameters (w), position-updating mechanism, and fitness-function all have an impact on PSO's performance. In our research, we experimented with changing and tweaking PSO settings. The weighting after adjustment may effect the features of the EKNN classifier and considerably increase classification accuracy via all of the tuning of the process parameters for PSO. The FS was able to cut classifier computation time and eliminate non-optimal features while maintaining classification accuracy. The EPSO-EKNN approaches surpassed the present DBN methods in terms of classifier Accuracy, Precision, and Recall, according to the findings of the testing. In the future, this research might be aided by focusing on segmentation and classification utilising sophisticated learning algorithms.

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