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Modified Particle Swarm Optimization and Machine Learning for Solving Handwritten English Characters

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The Handwritten English Recognition Problem (HERP) involves interpreting handwritten English text from sources such as documents and answer sheets. This problem is particularly challenging and complex due to the uniqueness of each person's handwriting, along with several factors that influence the interpretation process. Recently, many researchers have proposed using the Histogram of Oriented Gradients (HOG) technique or the combination of Discrete Wavelet Transform and Discrete Cosine Transform (DWT-DCT) for feature extraction. Additionally, researchers have explored machine learning techniques to address this problem, with experimental results showing that machine learning can effectively solve it. Therefore, this research proposes using machine learning methods such as Support Vector Machine (SVM), Random Forest (RF), and Logistic Regression (LR), combined with HOG or DWT-DCT for feature extraction, to tackle this challenge. Experimental results from this research indicate that SVM achieves the best outcomes. Consequently, this research enhances SVM by using Particle Swarm Optimization (PSO) to optimize SVM parameters, improving model performance and achieving a higher recognition rate. Experiments were conducted on two datasets: the EMNIST dataset and a personalized handwriting dataset from 30 participants. The results demonstrate that the proposed method, which employs HOG for feature extraction and PSO-optimized SVM, achieves superior accuracy compared to other methods, underscoring its effectiveness in HERP.

CCS CONCEPTS

Machine Learning; • Supervised Learning; • Image Processing; • Feature Extraction

Keywords

Handwritten English Characters, Particle Swarm Optimization, Machine Learning, Support Vector Machine

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1 INTRODUCTION

English is a globally used language, making the ability to read handwritten English text very important. This skill has numerous applications, including grading handwritten exams, translating handwritten documents, automatic number plate recognition, and assistive tools for the visually impaired and storing documents in digital format for easier future retrieval. Thus, HERP is both significant and widely applicable. This research is interesting and aims to address HERP. Handwritten Character Recognition (HCR) is the computer's ability to read, process, and convert handwritten text into a machine-readable format. HERP is a subset of HCR. Handwritten Digits Recognition (HDR) is a specific aspect of HCR, focusing solely on interpreting handwritten numbers, such as digits from 0 to 9 [1]. HCR can be divided into two categories [2, 3]. The first, Online Character Recognition, involves converting handwritten text into characters based on the order of writing. This method facilitates interpretation because the writing sequence helps identify characters. The second, Offline Character Recognition, involves extracting handwritten characters from scanned images. Due to the unique style of each person’s handwriting, this method is more complex than the online approach. This research is focused on addressing HERP within the Offline Character Recognition category. The Extended Modified National Institute of Standards and Technology (EMNIST) database [4] is a well-known dataset for handwritten English characters and digits, commonly used to evaluate the classification performance of algorithms. Recently, the EMNIST dataset has driven extensive research, contributing to the advancement of more efficient HCR methods. Recently, many researchers have been trying to solve HCR, employing various techniques such as Deep Learning (DL), Neural Networks (NN), SVM, and Hidden Markov Models (HMM), as follows: M. Geetha et al. [5] proposed deep learning algorithms, such as Convolutional Neural Networks (CNN) combined with Long Short-Term Memory (LSTM), to address HERP. Experimental results using the EMNIST dataset showed their model achieved an accuracy of about 81.8% for alphabets. P. V. Bhagyasree, A. James, and C. Saravanan [6] introduced a new deep learning technique called Directed Acyclic Graph Convolutional Neural Network (DAG-CNN) for HERP, achieving improved accuracy in experimental results. K. Kaur and N. K. Garg [7] proposed a 40-point metric method for feature extraction, using Neuron-Fuzzy and Weighted K-Means Algorithm for classification. Their techniques achieved relatively high accuracy for HERP. Ketan S. Machhale et al. [8] developed an offline HERP algorithm based on Artificial Neural Networks, achieving a maximum accuracy of 92.59% with their dataset. Ming Ma et al. [9] proposed an improved HMM-based recognition model for online English and Korean handwritten characters, achieving a high writer recognition rate of about 91.2% in their experiments. J. Pradeep et al. [10] used a hybrid feature extraction technique with neural network classifiers for offline HERP, achieving the highest recognition accuracy compared to other algorithms and identifying it as a suitable classifier. P. Dhande and R. Kharat [11] applied a convex hull algorithm for feature extraction and SVM for classification and recognition. J. Samleepant and C. Ratanavilisagul [12] introduced a novel feature extraction method using PSO for HDR, achieving high recognition rates on the MNIST dataset [13] and datasets of individual handwritten digits. C. Ratanavilisagul [14] modified the method in [12] by adding a mutation operation to the PSO process, improving reliability and classification performance across standard and practical use datasets. P. Ghadekar, S. Ingole, and D. Sonone [15] presented a hybrid approach combining Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) for feature extraction with SVM classifiers, achieving accuracies of 97.74% on the MNIST dataset and 89.51% on the EMNIST dataset. Experimental results reveal that DL techniques achieve the highest recognition rates with EMNIST datasets. However, dataset size significantly impacts effectiveness;

smaller datasets can reduce model accuracy, while larger datasets require more resources, slowing the training process. Real-world HCR applications need to accommodate new individuals with unique handwriting styles, requiring extensive character data and substantial computational resources for effective model training [16]. Thi Thi Zin and Takato Otsuzuki [17] conducted tests using HOG and Bag of Visual Words techniques, with experimental results indicating that HOG achieved notably higher recognition rates. Ritam Guha et al. [18] examined feature extraction techniques such as Distance-Hough Transform, HOG, and Modified Log Gabor Filter Transform, finding that HOG achieved the highest classification accuracy across multiple datasets. Building upon prior research, this study proposes the use of the HOG technique for HCR. The process of solving HCR involves image segmentation, feature extraction, and classification techniques. Image segmentation is the process of separating the text into individual characters. Feature extraction involves transforming the segmented character images into numerical representations by extracting important features. Classification then takes these numerical values from the feature extraction step to identify which character they represent. This research focuses on developing the feature extraction and classification steps only. Extreme Gradient Boosting (XGBoost) uses gradient-boosted decision trees [19]. Its benefits include high performance, suitability for large datasets, easy parameter adjustments, and effective handling of missing values. However, it can be computationally intensive, memory-heavy, and time-consuming, and it is also prone to overfitting, especially with small datasets. Support Vector Machine (SVM) aims to find the optimal hyperplane in an N-dimensional space to separate data points into different classes. Its advantages include effectiveness with non-linear data and high-dimensional feature spaces, good class separation, and suitability for moderately sized datasets. However, it has limited interpretability and requires careful parameter adjustment [20]. Logistic Regression (LR) predicts the probability of an instance belonging to a specific class by analyzing the relationship between two factors. It is widely used and generally provides good accuracy. However, it struggles with complex patterns, is best suited for small datasets, and is limited to linear relationships [20]. Random Forest (RF) creates multiple decision trees using random subsets of data and features. Its benefits include preventing overfitting, robustness, and high accuracy. However, it is more suitable for medium-sized datasets, can be computationally intensive, and adds complexity [20]. Optimizing the classifier parameters of SVM is crucial for achieving high recognition accuracy. Particle Swarm Optimization (PSO) is a Metaheuristics optimization algorithm inspired by the social behavior of bird flocking and fish schooling [21]. Recently, many researchers have recommended using heuristic and Metaheuristics algorithms to solve HCR and related problems. Algorithms like PSO [16, 22] and Ant Colony Optimization (ACO) [23, 24] have proven effective in tackling highly complex problems. PSO has been successfully applied to optimize parameters in various machine learning models [25].

This research aims to compare the effectiveness of classification techniques using XGBoost, SVM, LR, and RF to determine the most effective method for solving HERP. The experimental results show that SVM achieves the best performance compared to XGBoost, LR, and RF, indicating that SVM is suitable for addressing HERP. Additionally, this research compares the feature extraction performance of HOG and hybrid DCP with DWT techniques in the context of HERP. The results indicate that the HOG technique is more effective in solving HERP than the DCP and DWT techniques. However, SVM has a key drawback: parameter adjustment [26]. To address this drawback of SVM, this research proposes using PSO to optimize SVM parameters and further enhance model performance for solving HERP. Consequently, this paper suggests using HOG for feature extraction and SVM with parameter adjustment through PSO for classification.

Experiments are conducted on two datasets: the EMNIST dataset, which is a standard benchmark for HERP, and an individual handwriting dataset collected from 30 participants. The results indicate that the proposed method achieves the best performance for solving HERP compared to other similar methods.

The remainder of this document is structured as outlined below: Section 2 explains the background. Section 3 discusses the related works. Section 4 describes the proposed method. Section 5 presents the experimental results. Section 6 concludes this research and outlines directions for future development of this research.

2 BACKGROUNDS

2.1 Histogram of Oriented Gradient

N. Dalal and B. Triggs [27] proposed the HOG technique. The concept of HOG is to identify important and unique features from character images for further analysis. This research proposes using the HOG technique, and the details of the HOG process are explained as follows. HOG was initially developed for pedestrian detection in static images. Its fundamental concept involves describing the appearance and shape of local objects in an image by analyzing the distribution of intensity gradients or edge directions. Similar to edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts, HOG captures these characteristics. However, it stands out by computing this information across a dense grid of evenly spaced cells and using overlapping local contrast normalization to enhance accuracy.

2.2 Support Vector Machine

SVM is a supervised learning model used for classification and regression tasks. The core idea of SVM is to find the hyperplane that best separates the data into different classes [28, 29]. This hyperplane maximizes the margin between the classes. The decision function for SVM can be written as:

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b \tag{1}$$

Where α_i are the Lagrange multipliers, y_i are the class labels, x_i are the support vectors, $K(x_i, x)$ is the kernel function, and b is the bias term. The Radial Basis Function (RBF) kernel is a commonly used kernel in SVM, defined as:

$$K(x_i, x) = exp(-\gamma \|x_i - x\|^2) \tag{2}$$

Where γ is a parameter that determines the width of the Gaussian function. In this research, SVM with a linear kernel is used for initial experiments, while the RBF kernel is employed for experiments involving PSO to optimize SVM parameters. The linear kernel is computationally efficient and effective for linearly separable data, whereas the RBF kernel can handle non-linear relationships by mapping data into higher dimensions. The parameters of SVM using the RBF kernel include two key parameters [26]. The first parameter is "C" which is a hyper parameter in SVM that controls the error. A low value of C indicates low error, while a high value of C indicates high error. However, a low error does not necessarily mean that it has a good model. It depends on the dataset. The parameter γ (Gamma) is used with the Gaussian RBF kernel. If SVM use a linear or polynomial kernel, it do not use gamma. γ determines how much curvature. A high gamma results in more curvature, while a low gamma results in less curvature. The decision to tune for high or low gamma depends on the dataset. In this research, I use the scikit-learn library [30] to develop the algorithm. The default values for SVM are defined according to this reference [31].

2.3 Particle Swarm Optimization

The idea behind PSO comes from how groups of animals, like flocks of birds or schools of fish move together in nature. PSO is a random method used to find the best answers to problems. Just like these animals communicate to find food, PSO helps particles work together to locate the best answers. In this case, the 'food' represents the target answers the particles are trying to reach.

Each member of the group is called a particle and has its own position and velocity. These particles move through the search area based on their velocities, the best position found by any particle (called GBEST), and their own best position (called PBEST). PSO starts by randomly setting the positions and velocities of the particles. Then, it checks how good each particle's position is according to the goals of the optimization problem. In each round, every particle updates its position and velocity using the formula below:

$$V'_{i,d} = \varpi V_{i,d} + \eta_1 \mathrm{rand}()(P_{i,d} - X_{i,d}) + \eta_2 \mathrm{rand}()(G_{i,d} - X_{i,d}) \tag{3}$$

$$X'_{i,d} = X_{i,d} + V'_{i,d} \tag{4}$$

Where $X_{i,d}$ is the previous positions of the i-th particle in the d-th dimension, $X'_{i,d}$ is the current positions of the i-th particle in the d-th dimension, $V_{i,d}$ is the previous velocity of the i-th particle in the d-th dimension, $V'_{i,d}$ is the current velocity of the i-th particle in the d-th dimension, $P_{i,d}$ is the individual best position (PBEST) of the i-th particle in the d-th dimension, and $G_{i,d}$ is the global best position (GBEST) in the d-th dimension. ϖ is the inertia weight, η_1 and η_2 are acceleration constants. rand() denotes a uniformly generated random number within the range of [0, 1]. V_{max} is maximum velocity, and if the computed velocity of a particle exceeds this limit, it is replaced with the value of V_{max}. PSO has been successfully applied to optimize parameters in various machine learning models, including SVM**.** By finding optimal parameters, PSO can enhance the performance of the classifiers, leading to better recognition accuracy**.**

3 RELATE WORKS

P. Ghadekar, S. Ingole, and D. Sonone [15] proposed a method to enhance the accuracy of digit and letter recognition by employing a hybrid approach that combines DWT and DCT for feature extraction with k-nearest neighbors (KNN) or SVM classifiers. In summary, the workflow they presented is detailed as follows: It begins with the model creation or training phase, where they utilized the MNIST database for digit recognition and the EMNIST database for letter recognition. They applied DWT to decompose the images into sub-band frequencies and DCT to transform spatial data into frequency domain features. These features were then classified using KNN or SVM. Subsequently, the model testing phase involved using the trained model to evaluate performance against test data. The results indicated that the hybrid DWT-DCT approach achieved a recognition rate of 97.33% using KNN and 97.74% using SVM for the MNIST database, while achieving 88.56% with KNN and 89.51% with SVM for the EMNIST database. The hybrid DWT-DCT method was successful in reducing the number of features and computation time. The method that uses the hybrid DWT-DCT and SVM classifier is referred to as DWT-DCT + SVM.

4 PROPOSAL WORKS

The experimental results from the research by P. Ghadekar, S. Ingole, and D. Sonone [15] demonstrate that SVM has better model-building performance than KNN in both digit recognition and letter recognition. Therefore, this research recommends using SVM for model construction. Their proposed method has a weak point in the feature extraction process, as the purpose of using DWT-DCT is image compression, making it rarely suitable for object detection and image classification. Hence, this research proposes using HOG for feature extraction, as it is specifically designed to address object detection and image classification. Consequently, the resulting model demonstrates improved performance. Thus, this research proposes that the combination of HOG for feature extraction and the robust classification capabilities of SVM are effective in enhancing recognition performance. Additionally, the drawback of SVM is the need for careful parameter adjustment. Adjusting parameters to build an effective model can impact model performance. To enhance the efficiency of model building with SVM, this study proposes using PSO to optimize SVM parameters. Techniques like PSO can further improve classifier accuracy by finding the optimal settings for the model, leading to a model with a higher accuracy rate. The aim of this research is to achieve higher recognition accuracy for solving HERP compared to other machine learning methods, such as XGBoost, LR, RF, and SVM without PSO, and to demonstrate that PSO can enhance the performance of SVM for solving HERP. Additionally, this research examines the effectiveness of the feature extraction techniques DCT + DWT and HOG for solving HERP. The proposed technique for solving HERP includes data collection and preprocessing, feature extraction using HOG, classification using SVM, and optimization of SVM parameters using PSO. It is called HOG + SVM + PSO. The proposed technique consists of a total of 4 steps, summarized as follows:

Step 1: Initially, the original image is cropped to isolate a handwritten character within a single frame. Subsequently, image segmentation is used to trim the surrounding white space, ensuring that the characters are centered. The image is then resized to 20x20 pixels. Thinning is a technique that simplifies the input data by removing any dots or the outer layer of a character until it becomes a single pixel in width. Following this, the HOG technique is employed to extract crucial features. The use of HOG yields 64 features (a one-dimensional array of size 64) for each character, which are then rescaled using Min-Max Normalization.

Step 2: SVM is used to classify the extracted features. PSO optimizes the SVM parameters, specifically the regularization parameter C and the kernel parameter γ.

Step 3: The outcomes from earlier stages are the training phase, leading to the generation of the output model.

Step 4: The output model derived is utilized during the testing phase to assess the recognition accuracy of the model.

5 EXPERIMENTS AND RESULTS

5.1 Datasets

This research uses two datasets for all experiments. The first dataset is the EMNIST dataset, and the second dataset consists of handwritten English characters contributed by 30 volunteers, referred to as the

HECD. The EMNIST letter dataset is a collection of handwritten English alphabets, containing 128,000 images for training and 20,800 images for testing, which can be downloaded from [32]. In this experiment, I am using all 128,000 images for training and all 20,800 images for testing. In the preprocessing stage, the images within the EMNIST dataset are size to 28 x 28 pixels. The MNIST dataset is used for digit recognition and is similar in structure to the EMNIST dataset. The MNIST dataset contains 60,000 images for training and 10,000 images for testing. The HECD consists of 30 sets, with each set corresponding to the work of a different volunteer who filled out an A4-sized paper, resulting in characters ranging from A to Z, as shown in Figure 1, and it can be downloaded from [33]. The scanned papers were processed using a clean, dust-free scanner to ensure minimal interference with the model's recognition. The scanned files are in ".BMP" format, and the paper size is 1653 x 2338 pixels, with each paper containing 208 characters. Each paper has 13 characters per line. I use 5 papers or 1,040 characters for training and 1 paper or 208 characters for testing. The EMNIST dataset and MNIST dataset are employed as a standard benchmark for assessing algorithm performance, whereas HECD is utilized to demonstrate the practical applicability of the results.

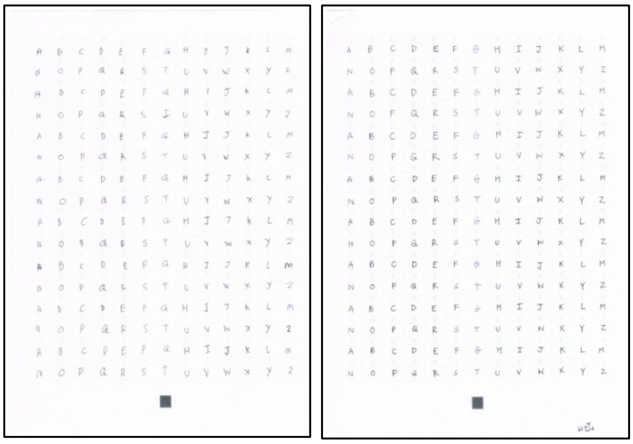

Figure 1: the individual's handwritten English Characters dataset example from volunteers.

5.2 The Measures of Algorithm Performance

The performance metrics used in the experiments are described as follows: The Recognition Rate is calculated as the percentage of correctly identified predictions divided by the total number of data points. The Recognition Rate serves as an indicator of the algorithm's classification performance, with higher Recognition Rate values corresponding to better classification performance. Time Test is the processing time per character in the testing phase, with the time unit being milliseconds. Time Train is the processing time per character in the Training phase, with the time unit being milliseconds.

5.3 Parameters Setting

The parameters used in all experiments are as follows: For the PSO parameters, the PYSWARMS Library [34] is utilized. All PSO parameters use the default settings from this library, except for the swarm size, which is set to 10, and the maximum number of iterations, which is also set to 10. The DWT and DCT parameters are configured based on the recommendations outlined in the original paper [15], while HOG, RF, XGBoost, LR, and SVM parameters are configured based on standard values from the scikit-learn library. For the SVM + PSO parameters, the bounds for C and γ are set to [1, 100] and [0, 10], respectively. These bounds are chosen to provide a reasonable range for the SVM parameters, ensuring that the search space is neither too broad nor too narrow, which helps in efficiently finding the optimal parameters. This research is conducted on a personal computer with an Intel i7-14700F CPU running at 2.1 GHz, 16 GB of RAM, and Python 3 as the programming language.

Table 1: Comparison of the recognition rates of XGBOOST, SVM, RF, LR, and SVM + PSO on EMNIST, MNIST and HECD.

Technique	EMNIST		HECD		MNIST	
	Recognition rate	Time Test	Recognition rate	Time Test	Recognition rate	Time Test
DWT-DCT + LR	69.73	0.131	95.27	0.005	88.50	0.001
DWT-DCT + RF	81.06	2.727	96.45	0.029	93.70	0.016
DWT-DCT + XGBOOST	84.48	0.347	96.53	0.012	95.30	0.006
DWT-DCT + SVM	89.51	141.211	97.32	0.163	97.74	2.953
DWT-DCT + SVM + PSO	99.98	169.348	99.89	0.17	99.98	3.057
HOG + LR	72.6	0.1	95.88	0.002	91.60	0.001
HOG + RF	87.03	1.949	97.88	0.028	95.10	0.071
HOG + XGBOOST	87.92	0.308	97.88	0.01	97.00	0.007
HOG + SVM	92.45	118.798	98.69	0.09	98.50	1.444
HOG + SVM + PSO	99.98	132.967	99.89	0.093	100	1.657

Table 2: Comparison of the parameters of SVM + PSO on EMNIST and HECD.

Technique	Swarm Size	Max Iteration	EMNIST		HECD	
			Recognition rate	Time Train	Recognition rate	Time Train
HOG + SVM + PSO	5	10	75.25	13.29	98.90	13.45
	10	10	99.98	17.78	99.89	29.09
	20	10	99.98	22.75	99.89	53.56
	10	5	0.7525	14.6	98.90	14.31
	10	20	99.98	20.12	99.89	51.79

The experimental results in Table 1 show that SVM surpasses LR, RF, and XGBoost in terms of classification performance with the same feature extraction methods, both DWT-DCT and HOG, as evidenced by its superior recognition rate across all datasets, including the EMNIST and HECD datasets. This indicates that SVM is effective in solving HERP on both a standard benchmark dataset and a practical applicability dataset compared to other machine learning techniques. Additionally, when comparing LR, RF, XGBoost, and SVM using different feature extraction methods, HOG achieves a better recognition rate than DWT-DCT across both the EMNIST and HECD datasets. This demonstrates that using HOG for feature extraction is more effective in solving HERP than using DWT-DCT. Moreover, SVM with PSO, which uses the same feature extraction method, surpasses SVM without PSO that employs the same feature extraction, as evidenced by its superior recognition rate across all datasets, including the EMNIST and HECD datasets. This indicates that using PSO to adjust parameters can enhance performance in solving HERP on both a standard benchmark dataset and a practical applicability dataset. Additionally, when the proposed method was tested on the MNIST dataset, which is a handwritten digits recognition dataset, the experimental results showed that the proposed method yielded the best results. The experiment on the MNIST dataset produced results similar to those from the experiment on the EMNIST dataset. The experimental results from all three datasets show that the proposed method requires slightly more processing time in the testing phase compared to SVM. The experimental results in Table 2 show that the parameter settings of PSO, with the swarm size and max iteration set to 10, are appropriate. Increasing these values does not improve the results but significantly increases the training time.

6 CONCLUSION

In this research, I proposed a method for solving HERP that uses HOG for feature extraction, SVM for classification, and PSO for parameter optimization of SVM. The performance of the proposed method was evaluated on two datasets: the EMNIST and HECD dataset. The experiments on the EMNIST and HECD datasets revealed that the solutions produced by the proposed algorithm outperform those obtained through comparisons with other algorithms, such as LR, RF, XGBoost, and SVM. Furthermore, PSO can further improve the performance of SVM. Therefore, the proposed method of combining HOG, SVM, and PSO provides the best results in terms of classification performance across various datasets, including both standard datasets and those reflective of practical usage. Moreover, this research conducted an experiment comparing feature extraction between HOG and DWT-DCT. The experimental results show that feature extraction using HOG is more suitable for solving HERP than feature extraction using DWT-DCT. In future plans, I intend to further develop the proposed algorithm to achieve even higher recognition rates. Future endeavors will involve introducing novel feature extraction techniques into the proposed algorithm. Additionally, the improved algorithm can be applied to extended datasets that include handwritten digits and mathematical signs, such as addition (+), subtraction (-), multiplication (×), and division (÷), as well as handwritten English (both uppercase and lowercase letters). This can also be applied to check homework in practice.

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