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Improving Character Recognition Accuracy with Meta-Heuristic Algorithms

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ABSTRACT

Background

Recognition of symbols and words is crucial in today's digital age, with Artificial neural networks algorithms (ANN) playing a significant role in this domain. The primary challenge addressed in this research is the need for a reliable and efficient system capable of achieving high accuracy in character recognition, despite varied font styles and minimal training data.

Materials and Methods:

Our study demonstrates combining Artificial Neural Networks with two Meta-Heuristic include Grasshopper and Propeller algorithms significantly improves accuracy of character recognition system. Many pre-processing techniques applying in order to achieve optimal segmentation of these character. After that, twenty-seven statistical features such as geometric, shape and size are extracted for capital and small alphabet character. Back-Propagation Learning Algorithm (BP) was used for training the ANN, optimising its performance and fine-tuning internal parameters over 1200 iterations.

Results:

This hybrid approach achieves high accuracy, more than 93% in both capital and small alphabet characters. The evaluation algorithms give 0.90 %Sensitivity and 0.93%Specificity.

Conclusions:

According to evaluation algorithms, the combining Artificial Neural Networks with two Meta-Heuristic algorithms achieves high accuracy character recognition.

Keywords: English Alphabet Recognition; Artificial neural networks algorithms(ANN); Grasshopper Optimization Algorithm; Character Recognition; Pattern Recognition.

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INTRODUCTION

Character recognition is an element of optical character recognition (OCR) systems serving a role, in various applications such as document processing and text extraction in digital settings[1]. The accurate identification of letters including both lower case characters poses a significant challenge especially when faced with different font styles and limited training data[2]. Over the decades there have been notable advancements in character recognition within the realms of pattern recognition and artificial intelligence[3]. Research has focused on handwriting detection exploring techniques like RNN HMM and leveraging tools like Tesseract, for open source OCR engines. Numerous studies have delved into methods to overcome the complexities associated with identifying characters across contexts[4,5].

Within the field of Optical Character Recognition (OCR) systems researchers have worked towards improving the precision and adaptability of recognition algorithms. Strategies have been developed to address varying handwriting styles and accommodate texts featuring fonts and styles [6,7]. Research has placed emphasis, on identifying handwriting exploring methods like RNN HMM [8]. Using OCR tools such as Tesseract [9]. *The goal of these studies is to establish handwriting recognition, for diverse languages and writing systems*.

License plate recognition systems have also gained attention, with researchers exploring methods based on fuzzy logic [10], and using feature extraction techniques such as Scale-Invariant Feature Transform (SIFT) [11]. These efforts seek to increase the accuracy and robustness of license plate identification, especially in challenging environments with noise and occlusions. In addition, studies focusing on specific languages and scripts have made significant contributions to character recognition research. For example, research into character recognition in Urdu, Gurmukh, Tamil, Javanese, and Bangla has led to the development of specialized models and algorithms tailored to these linguistic contexts [12-15].

Innovative approaches such as concept learning and region sampling have further expanded the horizons of feature recognition[16]. These methods offer new insights into feature extraction and classification, paving the way for more accurate and efficient recognition systems[17,18]. In addition, the evaluation of structural and statistical features in character recognition was of interest. Studies conducted experiments with Multilayer Perceptron (MLP) and Support Vector Machines (SVM) classifiers and investigated the impact of various attributes and optimization techniques on recognition accuracy[18,19].

Metaheuristic algorithms are optimization techniques used to solve complex problems that cannot be solved by traditional methods. Metaheuristic algorithms have proven to be particularly valuable in solving problems where traditional optimization techniques struggle due to the high dimensionality or non-linearity of the search space[20,21]. By mimicking natural phenomena and using population-based methods, these algorithms can efficiently traverse complex problem areas and find near-optimal solutions. Researchers are constantly improving and exploring metaheuristic algorithms to expand optimization and problem solving capabilities[22].

In summary, the character recognition literature reflects a diverse range of approaches and methodologies aimed at overcoming the challenges of character identification in different languages, scripts, and contexts. These studies contribute to the continued development of character recognition systems, facilitating advances in automation, information retrieval, and human-computer interaction, as shown in Table 1.

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Table 1: Summary of Character Recognition Methodologies with Accuracy, Advantages, and Disadvantage

Study	Methodology	Accuracy	Advantages	Disadvantages
RNN-HMM	Combination of RNN and HMM	High	Effective for sequence prediction; captures temporal dependencies	Computationally intensive; requires large datasets
Tesseract OCR	Utilization of Tesseract engine	Varied	Open-source; supports multiple languages	Limited accuracy for complex fonts and handwriting
Fuzzy logic-based methods	Fuzzy logic techniques	High	Handles uncertainty well; flexible	Can be complex to design; may require fine-tuning
SIFT feature extraction	Scale-Invariant Feature Transform	High	Robust to scale and rotation changes; effective for object recognition	Computationally expensive; high memory usage
Urdu character recognition	Specific models for Urdu	High	Tailored for language-specific nuances; high accuracy	Limited applicability to other languages; may require large training datasets
Gurmukhi character recognition	Specialized algorithms for Gurmukhi	High	Optimized for Gurmukhi script; accurate results	Not generalizable to other scripts; can be complex to implement
Tamil character recognition	Tailored models for Tamil	High	High accuracy for Tamil script; language-specific optimization	Limited to Tamil script; may require significant training data
Javanese character recognition	Specific methods for Javanese	High	Effective for Javanese characters; high recognition rate	Not applicable to other scripts; development complexity
Bangla character recognition	Customized approaches for Bangla	High	Accurate for Bangla script; specialized techniques	Script-specific; high implementation effort
Conceptual learning	Innovative learning techniques	High	Encourages deep understanding; adaptable	Can be difficult to implement; may require extensive data
Area sampling	Advanced sampling methods	High	Improves generalization; effective for varied datasets	Computationally intensive; may require complex setup
MLP and SVM classifiers	Neural network and SVM methods	High	Versatile; effective for many recognition tasks	Requires careful parameter tuning; computationally expensive
Integration of Grasshoppers into MLP	Advanced optimization techniques	High	Enhances performance; effective optimization	New and relatively untested; may be complex to implement

THE AIM AND OBJECTIVES OF THE STUDY

The aim of the study is to develop a character recognition system that, in spite of challenges brought on by a dearth of training data and variations in font design, can accurately identify English letters in both capital and lowercase forms.

To achieve this aim, the following objectives are accomplished:

- To create a multi-layer feed-forward neural network for character recognition: Construct a neural network architecture that is capable of recognizing English letters and accounting for variations in font styles.
- Utilize the Back-Propagation Learning (BP) Algorithm: Utilizing the BP approach, train the neural network, being especially mindful of parameter value optimization to enhance recognition performance.
- Include methods for optimizing meta-heuristics: Adjust the neural network parameters using the Propeller and Grasshopper optimization methods to solve sensitivity initial value problems.
- Analyze and clarify the results: Describe how the accuracy of the character recognition system is improved by combining the usage of the Grasshopper and Propeller algorithms, especially when dealing with a variety of font styles.

MATERIALS AND METHODS

The develop a character recognition system involves the process of identifying characters within an image and converting them into machine-readable formats. In this research apply Matlab software. It typically includes several steps as show in Figure 1. Start with pre-processing image in order to enhancing the input document by reducing noise and maximizing shape information to obtain a clean image. After that, segmentation processing apply in order to separating words, lines, or individual characters from the input image to facilitate accurate recognition. From the segmentation process, letters are obtained for extracting features. In feature extraction process extracting various features such as height, width, lines, strokes, etc., from each character to aid in classification. The data that generated from features using as input in classification process. In classification; using feed-forward multilayer Neural Networks algorithms to categorize the extracted features and recognize the characters. In order to enhance the recognition accuracy using Meta-Heuristic algorithms. As well as the Grasshopper algorithm used, it helps identify initial optimal regions, while the Propeller algorithm refines these regions, precisely determining the neural network parameters to achieve maximum accuracy. The purpose of used this algorithm to allows extending the modelling, where building a parametric model is to generate modifications. And variations quickly and to automate repeated modelling [23]. This combination results in a more robust and efficient character recognition system, especially when dealing with font variations in order to improve English letter recognition.

Finally, the output generation storing the recognized characters in a text format or other machine-readable representations.

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Pre-processing
Reducing noise and maximizing shape information to obtain a clean image.

Segmentation
Separating words, lines, or individual characters from the input image to facilitate accurate recognition

Feature Extraction
Extracting various features such as height, width, lines, strokes, etc., from each character to aid in classification

Classification
Using algorithms or models to categorize the extracted features and recognize the characters.

Output Generation
Storing the recognized characters in a text format or other machine-readable representations.

Figure 1. Character Recognition Overview

Datasets:

The primary dataset utilized in this study was sourced from Kaggle [24]. This dataset comprised 26 folders (A–Z), each containing 32 pixel-sized grayscale rendered alphabet characters, encompassing over 14,900 fonts. The dataset was diverse, including both uppercase and lowercase letters, thus offering a robust testing ground for character recognition.

Pre-processing:

Prior to training the neural network, the dataset underwent a series of preprocessing steps to enhance the quality of input data: Figure 2 show the pre-processing steps, each steps include algorithms or method.

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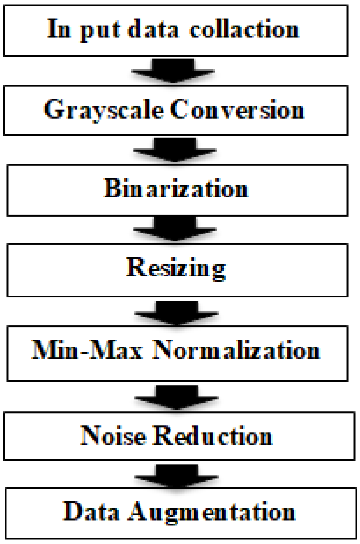

Figure 2. Pre-processing image character steps

– **Grayscale Conversion**: The images were converted to grayscale, simplifying data complexity and preserving essential contrast information.

– **Binarization**: in this step isolation background/character using minimum distance criteria and binary mask to make the thresholding technique more efficient to convert grayscale images into binary images, focusing on character shapes.

– **Resizing:** Images were resized to a consistent 15x15 pixel format, in this step using Bilinear interpolation method, this method applies to resample images and textures ensuring uniformity and reducing computational complexity.

– **Min-Max Normalization**: Pixel values were normalized to a scale of [0, 1], stabilizing training and improving convergence. Using normalization method to reduce the significance of differences in the range of raw data. This method places all feature values to be in the same range of values. The data ranged between (±1) as the outputs for (1) [25]. However, replicated data are not required

$$Z_i = \frac{x_1 - \min(x)}{\max(x) - \min(x)} \qquad (1)$$

where;
x= (x1, x2...,xn)
zi is the ith normalized data

– **Noise Reduction:** Techniques like blurring were applied to smoothing the color transition between the pixels using Gaussian Filter as shown in (2).

$$f(x, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \qquad (2)$$

where ;
μ: is a mean
σ: is a standard deviation
x: is the independent variable.

– **Data Augmentation**: the purpose of using this method to we increase the size of the training set artificially in ML algorithms. Images underwent rotations, flips, and scaling to augment the dataset, enhancing the network's robustness.

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Feature Extraction

Twenty-seven statistical extracting features are extracted from a character image. These features are Moments, Variance, and Standard Deviation, these are described by the following criterion Equation, respectively [26]. The features are extracted from gray image.

$$Mom(n) = \frac{1}{k}\sum_{i\in c}(x_i' + jy')^n \quad , \qquad n = 1,2 \tag{3}$$

Where;

$$x_i' = \frac{1}{L}\left[(x_i - \bar{x})\cos\theta - (y_i - \bar{y})\sin\theta\right]$$

$$y_i' = \frac{1}{L}\left[(x_i - \bar{x})\sin\theta + (y_i - \bar{y})\cos\theta\right]$$

$$\sigma^2 = \frac{\sum(xi - \bar{x})^2}{N} \tag{4}$$

$$\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{N}} \tag{5}$$

Where;

σ = population standard deviation

N = the size of the population

x_i = each value from the population

μ = the population mean

Optimization Algorithms:

Two meta-heuristic optimization algorithms were employed for fine-tuning neural network parameters:

– Grasshopper Algorithm: Emulated grasshopper behavior to explore solution spaces, balancing exploration and exploitation. It aided in identifying initial optimal regions in the solution space.

– Propeller Algorithm: A nature-inspired optimization algorithm used to further optimize the neural network's design. It refined solutions, ensuring precise parameter values for maximum accuracy.

Neural Network Configuration:

This method simulates the work of the human nervous system if you cut up the images of the letters you want to recognize and match them with pre-sound syllables. This method is characterized by the outstanding ability to recognize ordinary documents and even damaged texts in which letters appear in an unclear manner.

The Back-Propagation Learning Algorithm (BP) was used for training the neural network, optimizing its performance and fine-tuning internal parameters over 1200 iterations The neural network architecture consisted of three layers: an input layer with 120 neurons (15x15 pixels), a hidden layer with 60 neurons, and an output layer with 56 neurons, representing uppercase and

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lowercase letters. Activation functions included 'tansig' for the hidden layer and 'trainbfg' for the output layer. Training employed the Back-Propagation Learning Algorithm (BP) for 1200 iterations with a learning rate of 0.4.

In order to get optimal recognition, combines Grasshoppers and Propeller Algorithm optimization with neural network architecture. Aiming for superior accuracy, efficiency, and adaptability. This integration marks a new era of enhanced optimization in neural networks, pushing the boundaries of traditional methods. The complex interaction between Grasshoppers and MLP signifies a significant paradigm shift, leading to more reliable and precisely calibrated neural network models, and promising advancements in artificial intelligence.

Experimental Setup:

– Hidden Layer Neurons: 80 neurons in the hidden layer were chosen based on experimentation, balancing complexity and learning capacity.

– Training Rate: A rate of 0.6 was selected for stable convergence during Back-Propagation training.

– Grasshoppers: A population of 100 grasshoppers in the Grasshopper Algorithm ensured diverse exploration of solution spaces.

– Iterations: 150 iterations were conducted for optimizing MLP network parameters using the Grasshopper Algorithm.

– Consistency: The Grasshopper Algorithm was independently implemented 10 times to ensure consistent results.

Performance Evaluation:

To find the best practices for using neural network architectures. We performed several experiments, and the analysed the results. The accuracy, sensitivity and specificity of letter recognition was assessed using the following criterion Equation.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (7)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (8)$$

where TP represents True Positive, FP represents False Positive, TN represents True Negative and FN represents False Negative

RESEARCH RESULTS

The result of the English character recognition system show that the proposed technique achieves a remarkable accuracy of 94.9 % for recognizing capital letters and 93.2% for recognizing small letters of the alphabet using both meta-heuristic optimization algorithms. Also, the both algorithms give higher recognition in capital alphabet than small alphabet as show in Table 2.

Table 2. The accuracy recognition algorithms

Algorithm	Accuracy%	
	Capital Alphabet	Small Alphabet
ANN	**67.4**	**63.7**
ANN+Grasshoppers	**83.8**	**81.2**
ANN+Propeller	**87.4**	**82.1**
ANN + (Propeller,Grasshoppers)	**94.9**	**93.2**

Table 3. The ability of recognition algorithms

Algorithm	Sensitivity		Specificity	
	Capital Alphabet	Small Alphabet	Capital Alphabet	Small Alphabet
ANN	**0.6**	**0.61**	**0.69**	**0.66**
ANN + Grasshoppers	**0.8**	**0.81**	**0.88**	**0.83**
ANN + Propeller	**0.8**	**0.8**	**0.87**	**0.85**
ANN +(Propeller, Grasshoppers)	**0.9**	**0.93.2**	**0.93**	**0.942**

CONCLUSIONS

This study combines Artificial Neural Networks with two Meta-Heuristic algorithms to enhance the accuracy of character recognition systems. It utilizes 27 statistical features from both capital and small alphabet characters. The training dataset was augmented through image rotations, flips, and scaling to improve robustness. Pre-processing was conducted to reduce the algorithm's error rate. The Back-Propagation Learning Algorithm (BP) trained the ANN over 1200 iterations, resulting in over 93% accuracy for both character types. The performance of the discrimination algorithm showed high sensitivity (0.90%) and specificity (0.93%).

Conflict of interests.

There are non-conflicts of interest

References

[1] S., J. Karan, and Deepti Kakkar. "Chronological sewing training optimization enabled deep learning for autism spectrum disorder using EEG signal." *Multimedia Tools and Applications* pp. 1-28. 15 Feb. 2024. doi: 10.1007/s11042-024-18341-6

[2] Wu, Lei, Jiawei Wu, and Tengbin Wang. "Enhancing grasshopper optimization algorithm (GOA) with levy flight for engineering applications." *Scientific Reports* 13, no. 1 no.124. 2023.dol: 41598-022-27144-4

[3] D. Mohammad, E. Trojovská, and T. Zuščák. "A new human-inspired metaheuristic algorithm for solving optimization problems based on mimicking sewing training." *Scientific reports* vol.12, no. 1 pp 17387. 17 Oct. 2022. Doi: s41598-022-22458-9

[4] N. Jalil, M. Reza, F. Derakhshi, F. Razeghi, S. Mazaheri, Y. Zamani-Harghalani, and Rohollah Moosavi-Tayebi. "New hybrid method for feature selection and classification using meta-heuristic algorithm in credit risk assessment." *Iran Journal of Computer Science* . vol 3, pp.1-11.no.3, Jun. 2020. Doi: 333711179.

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[5] A. Prachi, F. Abutarboush, T. Ganesh, and Ali Wagdy Mohamed. "Metaheuristic algorithms on feature selection: A survey of one decade of research (2009-2019)." *Ieee Access* . vol. 9, pp. 26766-26791, 2021. Doi: 9344597

[6] D. Tansel, A. Deniz, and Hakan Ezgi Kiziloz. "A comprehensive survey on recent metaheuristics for feature selection." *Neurocomputing* vol. 494, pp. 269-296 July 2022. Doi: S092523122200474X.

[7] P. Lawrence D. M. Buede. "The Engineering Design of Systems–Models and Methods." No Wiley:pp. 58-59,2000. Doi: 10.1002/9780470413791

[8] C. Vinod Kumar, S. Singh, A. Sharma. "HCR-Net: A deep learning based script independent handwritten character recognition network." *Multimedia Tools and Applications* vol. 83, pp. 78433–78467.Feb 2024. Doi:10.1007/s11042-024-18655-5

[9] D., A., Bugeja, M., Seychell, D., & Mercieca, S. (2018). Recognition of handwritten characters using google fonts and freeman chain codes. In *Machine Learning and Knowledge Extraction: Second IFIP TC 5, TC 8/WG 8.4, 8.9, TC 12/WG 12.9 International Cross-Domain Conference, CD-MAKE 2018, Hamburg, Germany,* Springer International Publishing. pp. 65-78. Aug 2018.doi: 10.1007/978-3-319-99740-7_5

[10] A. Saman, M. Awaz, A. Shaban, Z. Arif Ali, Rasan Ismael Ali, and Jayson A. Dela Fuente. "Overview of metaheuristic algorithms." *Polaris Global Journal of Scholarly Research and Trends* 2, no. 2.pp. 10-32. 2023. DOI:10.58429/pgjsrt.v2n2a144.

[11] S.Pankaj, S. Raju. "Metaheuristic optimization algorithms: A comprehensive overview and classification of benchmark test functions." *Soft Computing* ,vol.28, no. 4 pp. 3123-3186. Oct.2024. doi: 10.1007/s00500-023-09276-5.

[12] A. Mohammadreza, S. Shaffiee Haghshenas, S. Mohammad Esmaeil Jalali, Shokrollah Zare, and Reza Mikaeil. "Developing the rule of thumb for evaluating penetration rate of TBM, using binary classification." *Geotechnical and Geological Engineering* vol.40, no. 9.pp. 4685-4703. May 2022.doi: 10.1007/s10706-022-02178-7.

[13] P. Raymond, F. Petroski Such, S. Pillai, Frank Brockler, Vatsala Singh, and Paul Hutkowski. "Intelligent character recognition using fully convolutional neural networks." *Pattern recognition.vol.* 88 pp.604-613. Apr. 2019.doi: S0031320318304370.

[14] J., Max, K. Simonyan, A. Vedaldi, A. Zisserman. "Synthetic data and artificial neural networks for natural scene text recognition." *arXiv preprint arXiv:1406.2227 . Dec 2014*

[15] Poznanski, Arik, and Lior Wolf. "Cnn-n-gram for handwriting word recognition." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2305-2314. 2016. doi.org/10.48550/arXiv.1406.2227.

[16] B. Shaojie, J. Zico Kolter, V. Koltun. "An empirical evaluation of generic convolutional and recurrent networks for sequence modeling." *arXiv preprint arXiv:1803.01271* . vol2. Mar 2018.doi: 1803.01271.

[17] A. Shashank. "Visual character recognition using artificial neural networks." *arXiv preprint cs/0505016*. May 2005.doi: 0505016.

[18] Suriya, S., S. Dhivya, and M. Balaji. "Intelligent character recognition system using convolutional neural network." *EAI Endorsed Transactions on Cloud Systems* .vol.6, no. 19 Oct.2020.doi: 16-10-2020.166659.

[19] R.N. Venkata, A. S. C. S. Sastry, A. S. N. Chakravarthy, and P. Kalyanchakravarthi. "Optical Character Recognition Technique Algorithms." *Journal of Theoretical & Applied Information Technology* ,vol.83, no. 2 . Nov.2016.

[20] V. Nisha, H. Jyotsana Parashar, S. Vijendra. "Offline character recognition system using artificial neural network." *International Journal of Machine Learning and Computing.*vol 2, no. 4. Aug, 2012. doi:10.7763/IJMLC.2012.V2.165.

[21] D. Patrick, M. Kozielski, H. Ney. "Fast and robust training of recurrent neural networks for offline handwriting recognition." In *2014 14th international conference on frontiers in handwriting recognition*, pp. 279-284. IEEE, 2014. DOI: 10.1109/ICFHR.2014.54

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[22] L. Chamila, T. Nadungodage, R. Weerasinghe. "Developing a commercial grade Tamil OCR for recognizing font and size independent text." In *2015 Fifteenth International Conference on Advances in ICT for Emerging Regions (ICTer)*, pp. 130-134. IEEE, 2015. DOI: 10.1109/ICTER.2015.7377678.

[23] F. Ali, Ali Al-Zawqari, A. Al-Qahtani, O. Hommos, Faycal Bensaali, A. Amira, and Xiaojun Zhai. "OCR based feature extraction and template matching algorithms for Qatari number plate." In *2016 International Conference on Industrial Informatics and Computer Systems (CIICS)*, pp. 1-5. IEEE, 2016. DOI: 10.1109/ICCSII.2016.7462419.

[24] K. Jong Woo, M. Messerschmidt, W. S. Graves. "Enhancement of Partially Coherent Diffractive Images Using Generative Adversarial Network." *AI* vol.3, no. 2 .pp.274-284. Apr. 2022.doi: 10.3390/ai3020017.

[25] A. Jameela Ali, Sh. Aziz Tome, L.E. George. "Classification of red blood cells using principal component analysis technique." *European Journal of Engineering and Technology Research*. vol.4, no. 2.pp. 17-22. Feb.2019. DOI:10.24018/ejers.2019.4.2.1007.

[26] A. Jameela Ali, R. Salih Mohammed Hasin, A. Zaki Naji, Loay E. George, and Sherna Aziz Tome. "Classification of Imbalanced leukocytes Dataset using ANN-based Deep Learning." In *Journal of Physics: Conference Series*, vol. 1999, no. 1, p. 012140. IOP Publishing, 2021. DOI 10.1088/1742-6596/1999/1/012140.

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الخلاصة

المقدمة:

يعد التعرف على الرموز والكلمات أمرًا بالغ الأهمية في العصر الرقمي اليوم، حيث تلعب خوارزميات الشبكات العصبية الاصطناعية (ANN) دورًا مهمًا في هذا المجال. التحدي الأساسي الذي يتناوله هذا البحث هو الحاجة إلى نظام موثوق وفعال قادر على تحقيق دقة عالية في التعرف على الحروف، على الرغم من تنوع أنماط الخطوط والحد الأدنى من بيانات التدريب.

طريقة العمل:

توضح دراستنا أن الجمع بين الشبكات العصبية الاصطناعية واثنتين من الاستدلالات الفوقية تشمل خوارزميات *Grasshopper* و*Propeller* تعمل على تحسين دقة نظام التعرف على الأحرف بشكل كبير. يتم تطبيق العديد من تقنيات المعالجة المسبقة من أجل تحقيق التقسيم الأمثل لهذه الشخصية. وبعد ذلك يتم استخراج سبعة وعشرين خاصية إحصائية مثل الشكل الهندسي والحجم للحرف الكبير والصغير. تم استخدام خوارزمية تعلم الانتشار الخلفي (*BP*) لتدريب *ANN* وتحسين أدائها وضبط المعلمات الداخلية لأكثر من 1200 تكرار.

النتائج:

يحقق هذا النهج المختلط دقة عالية، تزيد عن 93% في كل من الحروف الأبجدية الكبيرة والصغيرة. تعطي خوارزميات التقييم 0.90% حساسية و 0.93% خصوصية.

الاستنتاجات:

وفقا لخوارزميات التقييم، فإن الجمع بين الشبكات العصبية الاصطناعية وخوارزميتين ميتا-إرشادية يحقق التعرف على الأحرف بدقة عالية.

الكلمات المفتاحية:

التعرف على الأبجدية الإنجليزية. خوارزميات الشبكات العصبية الاصطناعية (*ANN*)؛ خوارزمية تحسين الجندب؛ التعرف على الحروف؛ التعرف على الأنماط.

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