Nature-inspired optimization algorithms and their significance in multi-thresholding image segmentation: an inclusive review

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Abstract
Multilevel Thresholding (MLT) is considered as a significant and imperative research field in image segmentation that can efficiently resolve difficulties aroused while analyzing the segmented regions of multifaceted images with complicated nonlinear conditions. MLT being a simple exponential combinatorial optimization problem is commonly phrased by means of a sophisticated objective function requirement that can only be addressed by nondeterministic approaches. Consequently, researchers are engaging Nature-Inspired Optimization Algorithms (NIOA) as an alternate methodology that can be widely employed for resolving problems related to MLT. This paper delivers an acquainted review related to novel NIOA shaped lately in last three years (2019–2021) highlighting and exploring the major challenges encountered during the development of image multi-thresholding models based on NIOA.

Keywords Multilevel Thresholding (MLT) · Nature-Inspired Optimization Algorithms (NIOA) · Exponential · Nonlinear · Combinatorial · Nondeterministic · Image segmentation

1 Introduction
Numerous practical applications entail the optimization of specific goals such as energy conservation, environmental protection and performance, efficiency, and long-term viability (Yang 2020). The optimization problems which can be framed in several circumstances are very complex, with multimodal objective landscapes and a collection of complicated, nonlinear constraints (Yang 2020). Solving such difficulties is challenging. Using basic brute force tactics remains unrealistic and undesirable, despite the rising capability of modern computers. As a result, efficient algorithms are critical in such applications wherever feasible. Unfortunately, efficient techniques may not present again for majority of application optimization problems. MLT-based image segmentation is an example of such problem in which a proficient search of the solutions inside a complex search area is required to discover the best solution (Dhal et al. 2020a). MLT is useful for generating two or more homogenous classes by segmenting composite images. The main procedure in the field of MLT is to determine the best threshold levels. Nevertheless, the MLT techniques have a major drawback in terms of the computation time that basically tends to increase as the number of thresholds grows, making it computationally demanding. Such flaws of MLT can be resolved by the Nature-Inspired Optimization Algorithms (NIOA) and it has become an imperative possibility. This inspiring nature has triggered the inquisitiveness in many academic scholars thereby focusing on the development of NIOA by conceptualizing natural events in computational terms. NIOA and their improved variants have proved its efficacy in engineering optimization problem and also resolving several MLT problems. Therefore, this study concentrates to accomplish an up-to-date review on recent NIOA and their MLT applications during past three years i.e., 2019–2021.

The remaining sections of the paper are systematized as follows: The review and discussion on recent NIOA since
2019 is presented in Sect. 2. The application of NIOA over MLT problem has been reported in Sect. 3. Section 4 highlights the experimental results of some newly developed NIOA in the year 2021. Lastly, Sect. 5 discusses on the conclusion and the future research directions.

2 Survey on recent nature-inspired optimization algorithms

Since millions of years, flora and fauna have showcased mechanisms to protect and secure their survivability when sources are scant (Li et al. 2020a). It’s realistic to opt these tactics for the prevalence and effectiveness while developing optimization algorithms. NIOA algorithms have offered a multitude of meta-heuristic algorithms for solving anticipated issues for the last few decades. According to the No Free Lunch (NFL) theorem, there exist no single NIOA that has the capability of solving all optimization problems (Dhal et al. 2019a, 2020a; Wolpert and Macready 1997). As a consequence, scholars are constantly proposing new NIOA, preserving the sector and propelling substantial progress year after year. In the work of Dhal et al. 2020a, the list of NIOA and their application in MLT domain has been reported up to the year 2018. Houssein et al. (Houssein et al. 2021a) published a book chapter in 2021 in the same topic but their research does not contain the recent full list of NIOA. The complete list of the developed NIOA in the period of 2019–2021 is reported in Table 1. In recent times, the combinatorial optimization field has perceived an over-flow with respect to "new" NIOA, the majority of which are based on some natural or artificial metaphor. Therefore, one only question that arises in the mind of the researchers when working in this field i.e., "which NIOA needs to be selected and focused on for the problem?". Therefore, the Table 1 also highlights the citation of the NIOA because citation can be a good metric for selecting NIOA from this huge set. It can be observed that in the year 2019, 2020 and 2021, around 22, 25, and 16 different NIOA respectively have been developed and proposed world-wide. However, such speedy progress and introduction of new NIOA makes the research tough in this field. Sorensen (Sörensen 2015) also wrote in his paper that this massive number of algorithms drags the field of NIOA a step backward rather than forward. His research also gained enormous popularity thereby achieving 726 citations according to Google scholar (dated 26.10.2021). As a consequence, the most critical question that arises in the mind of many today is “Does the scientific community need new NIOA’s or the existing NIOA’s are enough?”. There are already enough "novel" NIOA, according to the author of Sorensen (2015) and Fister et al. (2016), and there is no need to introduce additional NIOA. The time has arrived for standardization, to permit the research society to emphasis on more promising research avenues in the NIOA literature and to identify the true mechanics underlying in these "new" NIOA. The year wise number of published papers over NIOA based MLT has been presented in Fig. 1a.

On the other hand, no matter how rapid and massive is the evolution of Nature Inspired algorithm, NIOA is the scorching research area that has not just attracted several researchers but proved to be the most rapid growing field in research. Therefore, the introduction and designing of an integrated framework in terms of algorithm structure is advantageous for implementation. Over the last few years, a large body of literature has offered priceless insight into how to comprehend the applied tactics and what the NIOA’s general characteristics are (Dhal et al. 2019a, 2020a, b, 2021a). Based on the same, the common procedure of the NIOA is presented using flowchart depicted in Fig. 1b.

Most of NIOA follows the common flow comprising of four major steps as described in Fig. 1b. In Step 1, the population and its related initial parameters, representing possible solutions to the given optimization problem is initialized. Typically, random methods are applied to generate the initial parameter of the population ensuring that it conceals the solution space as much as possible. Based on the specific requirements of the experts and their past experience, the size of population (should be perhaps large) is selected. After initialization, in subsequent Step 2, the calculation in terms of the fitness value of an individual solution of population is performed and the concrete iteration loop starts, where every loop signifies a generation (Number of iterations). The fitness function which is most commonly considered as a unique pointer to echo the performance of each solution is premeditated by the help of the target function either comprising of the maximum value or minimum value. Commonly, each population has its own local optimal solution, and on the other hand, global optimum is owned by its complete population. The fitness values of the population are further computed in each of the iteration. Given the termination condition, if the global best solution satisfies the same, the output is generated (as shown in Step 4) else, Step 3 is instigated, that generally anticipates to accomplish the significant operations that is basically carried out for the purpose of information exchange amongst entire population to evolve excellent individuals. Further, updating in terms of population is carried thereby initiating the workflow to supplementary navigate towards Step 2 to accomplish the subsequent iteration. The generation counter is further amplified and till the stopping criteria is satisfied, the iteration undergoes. Stopping condition is a parameter that specifies when an algorithm should halt. For various NIOA, determining the stopping condition is critical. Number of Iterations, commonly known as NIs and number of Function Evaluations frequently known as FE's are two of the most prevalent types
| Sl | Name of the algorithm                          | Application area                                                                 | Author’s name                        | Year | Citation |
|----|-----------------------------------------------|-----------------------------------------------------------------------------------|--------------------------------------|------|----------|
| 1  | African Vulture’s Optimization Algorithm      | Mathematical and Engineering Optimization problems (Abdollahzadeh et al. 2021a)   | Abdollahzadeh et. al. (2021a)       | 2021 | 6        |
| 2  | Remora Optimization Algorithm                | Mathematical and Engineering Optimization problems (Jia et al. 2021)              | Jia et. al. (2021)                   | 2021 | 4        |
| 3  | Chameleon Swarm Algorithm                    | Mathematical and Engineering Optimization problems (Braik 2021)                  | Braik (2021)                         | 2021 | 8        |
| 4  | Artificial Gorilla Troops Optimizer           | Mathematical and Engineering Optimization problems (Abdollahzadeh et. al. 2021b), Solar Photo Voltaic Systems (Ginidi et al. 2021a), Image Segmentation (sayed et al. 2021) | Abdollahzadeh et. al. (2021b)       | 2021 | 5        |
| 5  | Flow Direction Algorithm                     | Mathematical and Engineering Optimization problems (Karami et al. 2021), (Karami et al. 2021) | Karami et. al. (2021)               | 2021 | 5        |
| 6  | Aquila Optimizer                              | Mathematical and Engineering Optimization problems (Abualigah et. al. 2021a), Oil Production Forecasting (AlRassas et al. 2021), Industrial Optimization Problem (Wang et al. 2021a)Abd Elaziz, Image Classification (Abd Elaziz et al. 2021b) | Abualigah et. al. (2021a)           | 2021 | 66       |
| 7  | QANA: Quantum-based Avian Navigation Optimizer| Mathematical and Engineering optimization problems (Zamani et al. 2021)          | Zamani et. al. (2021)               | 2021 | 1        |
| 8  | Atomic Orbital Search                         | Mathematical and Engineering Optimization problems (Azizi 2021), Feature selection (Elaziz et al. 2021) | Azizi (2021)                        | 2021 | 10       |
| 9  | Arithmetic Optimization Algorithm             | Mathematical and Engineering Optimization problems (Abualigah et. al. 2021b, Agushaka and Ezugwu 2021, Functionally Graded Material (FGM) plate structures (Khatir et al. 2021), MLT based Image Segmentation (Abualigah et al. 2021d), Feature Selection (Ibrahim et al. 2021; Ewees et al. 2021) Robot Path Planning (Wang et al. 2021b, Fog Computing (IoT) (Abd Elaziz et al. 2021c), PID controller (Izci et al. 2021) | Abualigah et. al. (2021b)           | 2021 | 160      |
| 10 | Dingo Optimizer                               | Mathematical and Engineering Optimization problems (Bairwa et al. 2021)           | Bairwa et. al. (2021)               | 2021 | 0        |
| 11 | Red Colobuses Monkey                          | Mathematical and Engineering Optimization design problems (Al-Kubaisy et al. 2021) | Al-Kubaisy et. al. (2021)           | 2021 | 0        |
| Sl | Name of the Algorithm | Application area | Author’s name | Year | Citation |
|----|-----------------------|------------------|---------------|------|----------|
| 12 | Archimedes Optimization Algorithm | Mathematical and Engineering Optimization problems (Hashim et. al. 2021), Wind Speed Forecasting (Zhang et al. 2021), Industrial Optimization (Yildiz et al. 2021), Wind Energy Generation System (Li et al. 2021), PEM Fuel Cell Parameter Identification (Houssein et al. 2021c; Sun et al. 2021a; Yao and Hayati 2021), Power Systems (Aribowo et al. 2021a), Feature Selection, Classification (Desuky et al. 2021; Chen and Rezaei 2021; Annrose et al. 2021; Neggaz and Fizazi 2021) | Hashim et. al. (2021) | 2021 | 58 |
| 13 | Rat Swarm Optimizer | Mathematical and Engineering Optimization problems (Dhiman et al. 2021), Image Classification (Vasantharaj et al. 2021), Deep Neural Network (Ghadge and Prakash 2021) | Dhiman et al. (2021) | 2021 | 49 |
| 14 | Hunger Games Search Optimizer | Mathematical and Engineering Optimization problems (Nguyen et al. 2021), (Onay and Aydemir 2022), (Chakraborty et al. 2022), Detecting Attacks (IoT Network) (Toğaçar 2021), Feature Selection (Devi et al. 2022) Abd Elaziz, Image Segmentation (Abd Elaziz et al. 2021d), PEM Fuel Cell Parameter Identification (Fahim et al. 2021) | Nguyen et al. (2021) | 2021 | 3 |
| 15 | Horse Herd Optimization Algorithm | Mathematical and Engineering Optimization problems (MiarNaeimi et al. 2021), Scheduling of Nanogrids (Basu and Basu 2021), Feature Selection (Awadallah et al. 2021) | MiarNaeimi et al. (2021) | 2021 | 10 |
| 16 | Preaching-inspired Optimization Algorithm | Mathematical and Engineering Optimization problems (Wei et al. 2021), MLT based image Segmentation (Wei et al. 2021), Wu et al (2021a) | Wei et. al. (2021) | 2021 | 2 |
| 17 | Battle Royale Optimization Algorithm | Mathematical and Engineering Optimization problems (Farshi 2021), Inverse Kinematics Problem (Farshi 2021) Agahian., Artificial Neural Network (Agahian and Akan 2021) | Farshi (2021) | 2021 | 14 |
| 18 | Child Drawing Development Optimization | Mathematical and Engineering Optimization problems (Abdulhameed and Rashid 2021) | Abdulhameed and Rashid (2021) | 2021 | 0 |
| 19 | Cat and Mouse Based Optimizer | Mathematical and Engineering Optimization problems (Dehghani et al. 2021) | Dehghani et. al. (2021) | 2021 | 0 |
| 20 | Tuna Swarm Optimization | Mathematical and Engineering Optimization problems (Xie et al. 2021a) | Xie et. al. (2021a) | 2021 | 0 |
| 21 | Past Present Future: a new Human-based Algorithm | Mathematical and Engineering Optimization problems (Naik and Satapathy 2021) | Naik and Satapathy (2021) | 2021 | 0 |
| 22 | Aptenodytes Forsteri Optimization Algorithm | Mathematical and Engineering Optimization problems (Yang et al. 2021a) | Yang et. al. (2021a) | 2021 | 0 |
| 23 | Bonobo Optimizer | Mathematical and Engineering Optimization problems (Das and Pratihar 2021) | Das et. al. (2021) | 2021 | 1 |
| Sl | Name of the algorithm            | Application area                                                                 | Author’s name                        | Year | Citation |
|----|----------------------------------|-----------------------------------------------------------------------------------|--------------------------------------|------|----------|
| 24 | Reptile Search Algorithm         | Mathematical and Engineering Optimization problems, Neuro-Fuzzy Inference System  | Abualigah et. al. (2021c)            | 2021 | 0        |
| 25 | Chimp Optimization Algorithm     | Mathematical and Engineering Optimization problems, Digital Filters, Neural Network, MLT based Image Segmentation, Feature Selection, Image Classification, Electrical Distribution Network, Power System Stabilizer, Solar Photovoltaic Systems, Solar Dish Sterling Power plant, Tunnel FET architecture | Khishe and Mosavi (2020a)            | 2020 | 87       |
| 26 | Slime Mould Algorithm            | Mathematical and Engineering Optimization problems, Artificial Neural Network, Solar Photovoltaic Systems, Servo Systems, MLT based Image Segmentation, Image Classification, Feature Selection, Numerical Optimization, Urban Water Resources, PEM Fuel Cell Parameter Identification | Li et al. (2020b)                   | 2020 | 363      |
| 27 | Gradient-based Optimizer          | Mathematical and Engineering Optimization problems, Photovoltaic Systems, Feature Selection, Image Classification, Feature Selection | Ahmadianfar et al. (2020)            | 2020 | 85       |
| 28 | Marine Predators Algorithm        | Mathematical and Engineering Optimization problems, Image Classification, Photovoltaic Systems, Fog Computing (IoT), Wind-Solar Generation System | Faramarz et al. (2020a)              | 2020 | 228      |
| 29 | Mayfly Optimization Algorithm     | Mathematical and Engineering Optimization problems, PEM Fuel Cell Parameter Identification, Deep Learning | Zervoudakis and Tsafarakis (2020)    | 2020 | 63       |
| Sl  | Name of the algorithm                      | Application area                                                                 | Author’s name                      | Year | Citation |
|-----|------------------------------------------|----------------------------------------------------------------------------------|-----------------------------------|------|----------|
| 30  | Manta Ray Foraging Optimization          | Mathematical and Engineering Optimization problems (Zhao et al. 2020a), Solar Cell based Systems (Fathy et al. 2020), Photovoltaic Systems (Houssein et al. 2021e), ECG Classification (Houssein et al. 2021f), MLT based Image Segmentation (Houssein et al. 2021g, Jena et al. 2021), Feature Selection Ghosh et al. 2021, Karuppusamy 2020, PEM Fuel Cell Parameter Identification (Xu et al. 2020), Waste Water Treatment plant (Elmaadawy et al. 2021), Thermo Electric Generation Systems (Aly and Rezk 2021), Deep Neural Network (Nguyen et al. 2021), Power Flow Problem (Kahraman et al. 2021), Photovoltaic / Diesel Generator / Pumped Water Reservoir Power System (Liu et al. 2021b), Electricity Theft Detection (Ayub et al. 2020), Inverted Pendulum System bin Abdul Razak et al. 2020), Distribution Network (Abdel-Mawgoud et al. 2021) | Zhao et al. (2020a)              | 2020 | 135      |
| 31  | Billiards-inspired Optimization Algorithm| Mathematical and Engineering Optimization problems (Kaveh et al. 2020a), Grid-Tied Wind Power Plants (Soliman et al. 2021), Construction Management (Rastegar Moghaddam et al. 2021), Ground-Water Systems (Gerey et al. 2021) | Kaveh et al. (2020a)             | 2020 | 21       |
| 32  | Equilibrium Optimizer                    | Mathematical and Engineering Optimization problems (Faramarzi et al. 2020b) (Gupta et al. 2020), MLT based Image Segmentation (Abdel-Basset et al. 2021a, Wunnava et al. 2020), Feature Selection (Gao et al. 2020, Too and Mirjalili 2021), Photovoltaic Systems (Abdel-Basset et al. 2020c), Fuel Cell Dynamic Model (Seleem et al. 2021; Menesy et al. 2020), Machine Learning (Kardani et al. 2021), Solar Dish Collector (Zayed et al. 2021b), Thermoelectric Power Generation Systems (Mansoor et al. 2021), Automatic Voltage Regulator System ((Micev et al. 2021) | Faramarzi et al. (2020b)           | 2020 | 327      |
| 33  | Coronavirus Optimization Algorithm       | Deep Learning and Electricity Load Time Series Forecasting (Martínez-Álvarez et al. 2020), Combinatorial Problems (El Majdoubi et al. 2021), PID Controller (Shamseldin 2021), Container Retrieval Problem (Silva Firmino and Times 2022), Image Classification (Nassif et al. 2021) | Martínez-Álvarez et al. (2020)     | 2020 | 48       |
| SI | Name of the algorithm          | Application area                                                                 | Author’s name                  | Year | Citation |
|----|--------------------------------|---------------------------------------------------------------------------------|--------------------------------|------|----------|
| 34 | Sparrow Search Algorithm       | Mathematical and Engineering Optimization problems (Xue and Shen 2020),       | Xue and Shen (2020)          | 2020 | 103      |
|    |                                | Photovoltaic Systems (Yuan et al. 2021), Proton Exchange Membrane Fuel Cell    |                                |      |          |
|    |                                | (PEMFC) Stacks (Zhu and Yousefi 2021), Robotic Path Planning (Zhang et al. 2021b), |                                |      |          |
|    |                                | UAV 3D Route Planning (Liu et al. 2021c), Deep learning (Liu et al. 2021c),    |                                |      |          |
|    |                                | Linear Antenna Array (Liang et al. 2021), Time-Series Production Forecasting  |                                |      |          |
|    |                                | (Li et al. 2022), Pulmonary Nodule Detection (Zhang et al. 2021c)               |                                |      |          |
| 35 | Sandpiper Optimization Algorithm| Mathematical and Engineering Optimization problems (Kaur et. al. 2020),       | Kaur et. al. (2020)          | 2020 | 10       |
|    |                                | Software Engineering (Amandeep et al. 2020), Deep learning (Rajalakshmi and  |                                |      |          |
|    |                                | Annapurani Panaiyappan 2021), (Metan et al. 2021).                           |                                |      |          |
| 36 | Black Widow Optimization Algorithm| Mathematical and Engineering Optimization problems (Hayyolalam and Kazem 2020), | Hayyolalam and Kazem (2020)  | 2020 | 126      |
|    |                                | MLT based Image Segmentation (Houssein et al. 2021h), (Al-Rahlawee and Rahebi  |                                |      |          |
|    |                                | 2021), Feature Selection (Hu et al. 2022), Internet of Things (IoT) (Ravikumar  |                                |      |          |
|    |                                | and Kavitha 2021), Wireless Sensor Networks (WSN) (Sheriba and Rajesh 2021),  |                                |      |          |
|    |                                | Human Object Detection (Mukilan and Semunigus 2021), Suspended Sediment Load  |                                |      |          |
|    |                                | Prediction (Panahi et al. 2021), Location-Inventory Routing Problem (Rahbari  |                                |      |          |
|    |                                | et al. 2021), PID Controller (Munagala and Jatoth 2021)                      |                                |      |          |
| 37 | Forensic-Based Investigation Optimization| Resource-Constrained Scheduling Problem (Chou and Nguyen 2020), Structural Design Problems Chou and Nguyen 2020, Mathematical and Engineering Optimization problems (Chou and Nguyen 2020, Kuyu and Vatansever 2021), Parameter optimization of support vector machine (Cao et al. 2021) | Chou and Nguyen (2020)         | 2020 | 17       |
| 38 | Bald Eagle Search              | Mathematical and Engineering Optimization problems (Alsattar et. al. 2020),   | Alsattar et. al. (2020)      | 2020 | 47       |
|    |                                | Photovoltaic Systems (Ramadan et al. 2021, Nicaire et al. 2021), Parameter    |                                |      |          |
|    |                                | optimization of support vector machine (Angayarkanni et al. 2021), Resource   |                                |      |          |
|    |                                | Management in Cloud Computing (Singh et al. 2019), Parameter optimization of  |                                |      |          |
|    |                                | Neural Network (Xie et al. 2021b), Internet of Things (IoT) (Kapileswar and  |                                |      |          |
|    |                                | Phani Kumar 2022)                                                           |                                |      |          |
| 39 | Life Choice-Based Optimization | Mathematical and Engineering Optimization problems (Khatri et al. 2020),      | Khatri et al. (2020)          | 2020 | 11       |
|    |                                | Visual Sentiment Analysis Afzal 2021)                                       |                                |      |          |
| SI | Name of the algorithm                  | Application area                                                                 | Author’s name                  | Year | Citation |
|----|--------------------------------------|----------------------------------------------------------------------------------|--------------------------------|------|----------|
| 40 | Social Ski-Driver Optimization        | Mathematical and Engineering Optimization problems, Feature Selection, Recurrent Fuzzy Neural Network, Autonomous Vehicle | Tharwat and Gabel (2020)       | 2020 | 37       |
| 41 | Gaining Sharing Knowledge-based Algorithm | Mathematical and Engineering Optimization problems, Feature Selection, MLT based Image Segmentation, Knapsack Problem, Photovoltaic Systems | Mohamed et al. (2020)          | 2020 | 65       |
| 42 | Artificial Ecosystem-based Optimization | Mathematical and Engineering Optimization problems, Identification of Hydro-geological Parameters, Fuel Cell Dynamic Model, Knapsack Problem, Photovoltaic Systems | Zhao et. al. (2020b)           | 2020 | 71       |
| 43 | Giza Pyramids Construction based Optimizer | Mathematical and Engineering Optimization problems, Image Clustering | Harifi et al. (2020a)          | 2020 | 15       |
| 44 | Heap-based Optimizer                  | Mathematical and Engineering Optimization problems, Industrial Solar Generation Systems, Fuel Cell Parameter Identification, Reactive Power Dispatch, DG allocation, Heat and Power Economic Dispatch Problem | Askari et. al. (2020a)         | 2020 | 51       |
| 45 | Color Harmony Algorithm               | Mathematical and Engineering Optimization problems, Interior Design | Zaeimi and Ghoddosian (2020)   | 2020 | 10       |
| 46 | Stochastic Paint Optimizer            | Mathematical and Engineering Optimization | Kaveh et al. (2020b)           | 2020 | 8        |
| 47 | Political Optimizer                   | Mathematical and Engineering Optimization problems, Feature Selection, Antenna Arrays, Fuel Cell Parameter Identification, Energy-Management System for Microgrids, Industrial Optimization problems | Askari et.al. (2020b)          | 2020 | 59       |
| SI  | Name of the algorithm          | Application area                                                                 | Author’s name                          | Year  | Citation |
|-----|--------------------------------|----------------------------------------------------------------------------------|----------------------------------------|-------|----------|
| 48  | Water Strider Algorithm        | Mathematical and Engineering Optimization problems (Kaveh and Eslamlou 2020, (Kaveh et al. 2020c), Structural Health Monitoring (Kaveh and Eslamlou 2020), Damage Detection (Ali et al. 2021) | Kaveh and Eslamlou (2020)              | 2020  | 42       |
| 49  | Newton Metaheuristic Algorithm | Mathematical and Engineering Optimization problems (Gholizadeh et al. 2020), Optimal placement and sizing of PV source (Montoya et al. 2021), Sizing optimization of Truss Structures (Danesh and Jalilkhani 2020) | Gholizadeh et al. (2020)               | 2020  | 22       |
| 50  | Harris Hawks Optimization      | Mathematical and Engineering Optimization problems (Heidari et al. 2019), Photovoltaic Systems (Chen et al. 2020), Design and Manufacturing Problem (Yildiz et al. 2019), Artificial Neural Network (Moayedi et al. 2021), Feature Selection (Turabieh et al. 2021, Hussain et al. 2021), MLT based Image Segmentation (Rodriguez-Esparza et al. 2020) | Heidari et al. (2019)                  | 2019  | 1019     |
| 51  | Sailfish Optimizer             | Mathematical and Engineering Optimization problems (Shadravan et al. 2019), Feature Selection (Ghosh et al. 2020), Wireless Sensor Networks (WSN) (Dao et al. 2020), Optimal STATCOM Allocation (Samal and Roshan 2020), Fibre Optic Communication (Venu et al. 2021) | Shadravan et al. (2019)                | 2019  | 129      |
| 52  | Pathfinder Algorithm           | Mathematical and Engineering Optimization problems (Yapici and Cetinkaya 2019), Fuel Cell Parameter Identification (Gouda et al. 2021), Optimal Reactive Power Dispatch problems ((Yapici 2021) | Yapici and Cetinkaya (2019)            | 2019  | 95       |
| 53  | Seagull Optimization Algorithm | Mathematical and Engineering Optimization problems (Dhiman and Kumar 2019), PEM Fuel Cell Parameter Identification (Cao et al. 2019), Feature Selection (Jia et al. 2019) (Ewees et al. 2022), Job Scheduling in Cloud (Garg and Dhiman 2021), Chemical Descriptors Classification (Houssein et al. 2021i) | Dhiman and Kumar (2019)                | 2019  | 208      |
| 54  | Booster Algorithm              | Mathematical and Engineering Optimization problems (Pakzad-Moghaddam et al. 2019) | Pakzad-Moghaddam et al. (2019)         | 2019  | 11       |
| 55  | Henry Gas Solubility Optimization | Mathematical and Engineering Optimization problems (Hashim et al. 2019), Feature Selection (Neggaz et al. 2020), Task Scheduling in Cloud Computing (Abd Elaziz and Attiya 2021), Prediction of Soil Shear Strength (Ding et al. 2021) | Hashim et al. (2019)                   | 2019  | 203      |
| Sl | Name of the algorithm          | Application area                                                                 | Author’s name                  | Year | Citation |
|----|--------------------------------|----------------------------------------------------------------------------------|--------------------------------|------|----------|
| 56 | Sea Lion Optimization          | Mathematical and Engineering Optimization problems (Masadeh et al. 2019), Underwater Acoustic Sensor Network (Kumar Gola et al. 2021), Cloud Computing (Masadeh et al. 2019), Deep Learning (Kumaraswamy and Poonacha 2021), Wireless Sensor Networks (WSN) (George and Mary 2021) | Masadeh et al. (2019)          | 2019 | 52       |
| 57 | Naked Mole-Rat Algorithm       | Mathematical and Engineering Optimization problems (Salgotra and Singh 2019, Salgotra et al. 2021), Wireless Sensor Networks (WSN) (Singh et al. 2021), Feature Selection (Guha et al. 2020), Antenna array (Singh et al. 2022), Electromagnetic Design Problems (Taherdangkoo 2021) | Salgotra and Singh (2019)      | 2019 | 49       |
| 58 | Nuclear Reaction Optimization  | Mathematical and Engineering Optimization problems (Wei et. al. 2019)             | Wei et. al. (2019)             | 2019 | 14       |
| 59 | Atom Search Optimization       | Mathematical and Engineering Optimization problems (Zhao et. al. 2019), Feature Selection (Too and Abdullah 2020), Antenna array (Almagboul et al. 2019), PID Controller (Zhao et al. 2021d), Fuel Cell Parameter Identification (Agwa et al. 2019) | Zhao et. al. (2019)            | 2019 | 148      |
| 60 | Search and Rescue Optimization | Mathematical and Engineering Optimization problems (Shabani et. al. 2019), Feature Selection and classification (Houssein et al. 2022) | Shabani et. al. (2019)         | 2019 | 30       |
| 61 | Wildebeest Herd Optimization   | Mathematical and Engineering Optimization problems (Amali and Dinakaran 2019), Predicting optimal hydropower generation (Ren et al. 2021), Deep Learning (Zhou and Arandian 2021) | Amali and Dinakaran (2019)     | 2019 | 6        |
| 62 | Butterfly Optimization Algorithm | Mathematical and Engineering Optimization problems (Arora and Singh 2019), Automobile Suspension Design (Yildiz et al. 2020), Feature Selection (Long et al. 2021), Data Classification (Jalali et al. 2019), Breast Cancer Prediction (Thawkar et al. 2021) | Arora and Singh (2019)         | 2019 | 367      |
| 63 | Blue Monkey Optimization       | Mathematical and Engineering Optimization problemsMahmood and Al-Khateeb (2019), Encrypting Digital Watermark (Abdulhammed 2021) | Mahmood and Al-Khateeb (2019)  | 2019 | 10       |
| 64 | Emperor Penguins Colony Optimizer | Mathematical and Engineering Optimization problems(Harifi et. al. 2019), Neuro-Fuzzy Systems (Harifi et al. 2020b), Inventory Control Systems (Harifi et al. 2021) | Harifi et. al. (2019)          | 2019 | 50       |
| 65 | Future Search Algorithm        | Mathematical and Engineering optimization problems (Elsisi 2019)                  | Elsisi (2019)                  | 2019 | 15       |

Number of NIOA in 2021 is 24, 2020 is 25, and 2019 is 16
Citation as per Google Scholar (Dated: 06.10.2021)
of stopping criteria. According to recent surveys, researchers prefer FEs to NIs (Dhal et al. 2020b).

2.1 Major challenges and problems with NIOA

Though there are immense number of researches and breakthroughs in regard to NIOA, it still has quite a few noteworthy challenges which can be pointed out by the following set of questions, especially from theoretical perspectives (Yang 2020):

1. Question on Mathematical Framework: How can a uniform mathematical framework be created so as to learn much about their convergence, convergence rate, consistency, and reliability? In reality, the core progressions of how such algorithms function, why it functions and under what circumstances are yet unknown and still mysterious.

2. Question on setting of NIOA’s parameters optimally: How to set the parameters of the NIOA to achieve efficient outcome for a set of problems? How can these parameters be meticulously changed or controlled to improve an algorithm’s performance?

3. Question on importance of Benchmarking and NFL Theorem: The usage of benchmark functions to examine the performance of the new NIOA in contrast to other existing algorithms is of utmost importance. On the other hand, the NFL theorem asserts that if algorithm A outperforms algorithm B in achieving the best optimal values of certain objective functions, then B will outperform A on other functions. However, from experience the interpretation can be made that some algorithms are superior to others. So, how to reconcile these seeming inconsistency? Therefore, the questions are: What are different varieties of benchmarking that turns out to beneficial? Free lunches do exist or not? If so, what could be the available circumstances?

4. Question on Performance Measures: The present literature primarily focuses on accuracy, computing effort, stability, and success rates as the performance indica-
tors. In general, Friedman test and the Wilcoxon’s rank sum test which are the widely accepted non-parametric tests can be used to compare and analyze efficiency among NIOA (Dhal et al. 2020b). However, it is unclear whether the aforementioned performance indicators are genuinely fair in comparison. Therefore, the questions are: What performance metrics can be considered in order to compare all the existing algorithms fairly? Is there any kind of possibilities to formalize a sole framework that allows entirely available algorithms to be related impartially and objectively?

5. Questions on Algorithm Scalability: The most crucial indicator of an algorithm’s efficacy from the standpoint of application is how well it can tackle a wide range of issues. Therefore, the question is: How can algorithms that work effectively for small-scale problems is scaled up to efficiently handle truly large-scale, real-world challenges?

Apart from the above-mentioned issues, other ongoing difficulties with NIOA includes finding the best combination of exploitation and exploration, dealing successfully with non-linear restraints, and applying these algorithms (NIOA) to machine learning techniques especially deep learning.

3 Recent trends in multi-level thresholding using nature-inspired optimization algorithms

It is reported in literature that when two or more segmentation approaches work together, they can yield better results than if they worked alone (Dhal et al. 2020a; Khan 2013).

Multi-thresholding is computationally expensive combinatorial task that entail large and complex search spaces. The evaluation of all feasible outcomes leads to a time-consuming search process. As a result, researchers incorporated NIOA, a powerful search tool, in this domain to make it less complicated and fast. This section gives a brief mathematical formulation of MLT problem; general algorithm of the NIOA based MLT, literature survey on MLT since 2019, and the objectives functions which play crucial role for proper image segmentation.

3.1 Introduction to multi-level thresholding

The central concept behind multi-level thresholding is to identify threshold values which allow the segmented images to fulfill the required criteria. This would be accomplished by optimizing specific objective function/s, with the threshold values as input parameters (Dhal et al. 2020a).

Assume that the image \( f \) of length \( L \) gray levels needs to be segmented into \( p \) partitions \( \{C_1, C_2, \ldots, C_p\} \) using set of \( (p - 1) \) threshold values \( TH = \{t_1, t_2, \ldots, t_{p-1}\} \), where \( t_1 < t_2 < \ldots < t_{p-1} \). For example, \( L = 256 \) for an 8-bit image and the grey levels are between 0 and 255 (Dhal et al. 2020a). Hence, a pixel containing certain gray level \( g \) belongs to class \( C_i \) if \( t_{i-1} < g < t_i \) for \( i = 1, 2, \ldots, p \).

The technique of determining the set of optimal thresholds \( TH^{opt} \) that optimizes the objective function \( F(TH) \) is referred to as single objective thresholding. The mathematical expression is as follows:

\[
TH^{opt} = \arg \max_{0 \leq TH \leq L-1} \min \{F(TH)\}. \tag{1}
\]

| SL | Type | Objective function |
|----|------|---------------------|
| 1  | 1-Dimensional objective functions | Otsu (Ray et al. 2021), Kapur’s entropy (Ray et al. 2021), Tsallis entropy (Ray et al. 2021), Cross entropy (Ray et al. 2021), Rényi entropy (Oliva et al. 2020), Fuzzy entropy (Dhal et al. 2019b), Type-II Fuzzy Entropy (Mahajan et al. 2021), Exponential Cross Entropy (Zhang et al. 2011), Kaniadakis Entropy (Lei and Fan 2021), Masi Entropy (Bhandari and Rahul 2019), t-Entropy (Chakraborty et al. 2021), Shannon entropy (Rajinikanth et al. 2021; Gong et al. 2020) |
| 2  | Hybrid and modified 1-dimensional objective functions | Fuzzy-Tsallis entropy (Sarkar et al. 2013), Fuzzy Masi Entropy (He et al. 2021), Tsallis–Havrda–Charvát entropy (Borjigin and Sahoo 2019) |
| 3  | 2-Dimensional objective functions | 2-Dimensional Kapur’s Entropy (Lei and Fan 2021), 2-dimensional Kullback–Leibler (K–L) (Zhao et al. 2016), 2-dimensional Otsu method (Bhandari and Kumar 2019), 2-dimensional Tsallis entropy (Sarkar and Das 2013), 2-dimensional Rényi entropy (Borjigin and Sahoo 2019), 2-dimensional Cross entropy (Akay 2013), Diagonal Class Entropy (DCE) (Xing and Jia 2019), 2-dimensional Masi entropy (Lei and Fan 2021; Naik et al. 2021), 2-dimensional Fuzzy entropy (Wu et al. 2004), Non-local 2-dimensional histogram-based entropy (Vig et al. 2019), 2-dimensional Kaniadakis entropy (Lei and Fan 2021) |
| 4  | 3-Dimensional objective functions | 3-Dimensional Otsu (Bhandari and Kumar 2019), 3-Dimensional Tsallis (Jena et al. 2021) |
| 5  | Other objective functions | Gaussian Mixture Model based objective function ( Cuevas et al. 2020), Wavelet entropy (Öztürk et al. 2020) |
| 6  | Energy curve based objective functions | Energy-Otsu (Bhandari and Kumar 2019), Energy-Masi (Bhandari and Rahul 2019), Energy-Cross (Kandhway and Bhandari 2019b), and Energy-Tsallis (Liang et al. 2019) |
For multi objective MLT, \( F(TH) = (F_1(TH), F_2(TH), \ldots, F_n(TH), \ldots, F_n(TH)) \), where \( n > 1 \).

### 3.2 Objective functions

In the theme or context of Multi-Level Thresholding-based image segmentation, objective functions are crucial. Few widely employed objective functions that have been presented in the existing literature. Objective functions in Table 2 categorized into some classes such as Variance based like Otsu, 1-Dimensional histogram-based entropies like Kapur’s entropy, 2-Dimensional histogram based objective functions, 3-dimensional objective functions, hybrid objective functions like Fuzzy-Tsalli’s entropy. Finding novel objective functions or the optimum objective functions for various image kinds is likewise a difficult task. Recently, some entropy based objective functions have been devised for MLT based image segmentation like t-entropy, and Masi entropy. According to the research, the segmentation efficacy of objective functions is strongly influenced by the issue domain, i.e., image type. Figure 2 depicts the number of papers Surveyed using different types of objective functions in the last three years recorded in Table 3.

From Fig. 2, it can be seen that Kapur’s entropy and Otsu maintain their popularity as objective function till date where some other new objective function have been developed. Now, a brief mathematical implementation of Kapur’s entropy has been given below for the help of the reader relate better to the Optimization being performed.

Kapur method (Ray et al. 2021) considers the combination of a probability distribution function of a given histogram with the concept of entropy. The principal idea behind this method, aims to find the best threshold combination that maximizes the entropy. Considering a binary class segmentation problem, the objective function for Kapur’s entropy is defined by:

\[
\begin{align*}
 f(th) &= \max\left(H_1(th) + H_2(th)\right), \\
 H_1(th) &= \sum_{i=1}^{th} \frac{P_{h_i}}{w_1(th)} \ln \left(\frac{P_{h_i}}{w_1(th)}\right), \\
 H_2(th) &= \sum_{i=th+1}^{L} \frac{P_{h_i}}{w_2(th)} \ln \left(\frac{P_{h_i}}{w_2(th)}\right),
\end{align*}
\]

where \( i \) represents the intensity of a given pixel such that \( 0 \leq i \leq L- \); \( NP \) represents the total number of pixels; \( h \) indicates the image histogram; \( h_i \) indicates the quantity of pixels having \( i \) intensity; and \( P_{h_i} \) is the probability distribution of the \( i \)-th level which is defined as:
Table 3 Literature reports on NIOA based multi-level thresholding

| SL | Proposed method | Objective function | Paper details | Image type | Comparison | Quality parameters considered | Observations |
|----|-----------------|-------------------|---------------|------------|------------|-------------------------------|--------------|
| 1  | Random Spare Strategy & Chaotic Intensification Strategy based on ACOR (RCACO) | 2D Kapur’s entropy | Zhao et al. (2021a) | Standard Color Images | Proposed method is compared with BA, ACOR, CS via Lévy flights, WOA, PSO, BLPSO, CGPSO, IWOA and IGWO | PSNR, SSIM and FSIM | Proposed RCACO attained quicker convergence speed along with accuracy to step out of Local Optima (LO). The obtained result proved that image segmentation quality is highly improved using the same. |
| 2  | Diffusion Association Slime Mould Algorithm (DASMA) | Renyi’s entropy | Zhao et al. (2021b) | Computed Tomography (CT) Images: Medical Images | Proposed method is compared with IGWO, IWOA, DE SSA, SMA, CS via Lévy flights and CGPSO | PSNR, SSIM and FSIM | Proposed DASMA at different threshold levels outperforms other algorithm thereby enhancing the convergence capabilities and segmentation performance. |
| 3  | CrissCross Ant Colony Optimization (CCACO) | 2D Kapur’s entropy | Zhao et al. (2021c) | Standard Color Images | Proposed method is compared with DE, WOA, GWO, PSO, SCA, ACOR, HHO, m_SCA, IGWO, CGPSO, OBLGWO, ALCPSO, BMWOA, ACWOA, SCADE and AMFO | PSNR, SSIM and FSIM | Proposed CCACO converge faster and accurately than ACOR thereby possess strong ability to avoid falling into LO. CCACO is considered very effective in terms of optimizing various benchmark functions. However, on the other hand computational complexity inexorably upsurges further, mounting the CPU computational time. |
| 4  | An MLS (Multi-Learning System) with Bat Algorithm for preprocessing, Shannon Entropy for multi-thresholding, Gaussian Filter for Image Enhancement, GLCM for Feature Extraction and SVM with Linear Kernel as Classifier | Shannon Entropy | Rajinikanth et al. (2021) | Retinal Images: Medical Images | The proposed MLS system uses SVM classifier that is compared with other classifiers: NB, DT, KNN and RF | Accuracy, FNR, FPR, Precision, NPV Sensitivity, F1-Score and Specificity | Experimental outcome of this research confirms that, SVM classifier offers superior accuracy (> 93%) compared to other classifiers considered in this study. |
| SL | Proposed method | Objective function | Paper details | Image type | Comparison | Quality parameters considered | Observations |
|----|-----------------|-------------------|---------------|------------|------------|-------------------------------|--------------|
| 5  | Infrared Pedestrian Segmentation Algorithm | 2D Renyi’s, 2D Kaniadakis entropy | Lei and Fan (2021) | Infrared Images | Proposed method is compared with 2D-Otsu, FCM, 2D-Masi, FLICM and 2D Kapur Entropy | ME, PSNR, Jaccard, RAE and F-measure | The proposed algorithm when applied to on the images with noise and intricate background produces better results when compared to 1D Kaniadakis and other five state-of-the-arts image segmentation methods |
| 6  | Moth-Flame Optimization (MFO) Algorithm | Kapur’s entropy | Ji and He (2021) | Standard Gray Images | Proposed method is compared with BA, PSO, FPA, MSA and WWO | Fitness value, Execution time, PSNR and SSIM | The proposed MFO is better in terms of convergence speed, stability, accuracy and segmentation effect. MFO could be further used to settle complicated high-threshold or color image by using different other objective functions |
| 7  | Gradient Based Method (GM) tailored for discrete objective function | Otsu’s thresholding and Kapur entropy | Shang et al. (2021) | Standard Gray Images | Proposed method is compared with FA, PSO, ABC, BA and GWO | PSNR, FSIM, IRU and CPU Time | The proposed GM is straightforward and simple to search for optimal threshold. Also, GM may be employed to search for optimal solution in more objective functions |
| 8  | Type-2 Neutrosophic-Entropy (T2NSEIF) | Kapur Entropy | Singh (2021) | MRI: Medical Images | Proposed method is compared with FCM, MFCM, FKMCA, KIFECM and NEATSA | JSC, CC, UM, Space and CPU time | The proposed T2NSEIF is employed to perform MRI’s segmentation using multiple thresholds with respect to locations of max T2NSE values. Further, other fields of Image Processing could be explored using the proposed method |
| SL | Proposed method | Objective function | Paper details | Image type | Comparison | Quality parameters considered | Observations |
|----|-----------------|--------------------|---------------|------------|------------|-------------------------------|--------------|
| 9  | Neighborhood Fitness Distance Ratio Teaching Learning based Optimization (NFDR-TLBO) | Kapur Entropy | Jiang et al. (2021a) | Standard Gray and Color Images | Proposed method is compared with TLBO, FDRPSO, FDR-TLBO, BBPSO, jDE and SaDE | PSNR, SSIM and FSIM | The proposed NFDR-TLBO algorithm shows exceptional result in most of the cases by suggestively improving TLBO. Though, more research and experiments need to be carried out to determine suitable objective functions to finally regulate optimal threshold values |
| 10 | Modified Whale Optimization Algorithm (MWOA) | Otsu’s thresholding and Kapur entropy | Anitha et al. (2021) | Standard Color Images | Proposed method is compared with GA, PSO, ABC and CS | PSNR, SSIM, FSIM and CPU time | The proposed MWOA offers improved performance as compare to other algorithms consuming a reduced amount of computational time |
| 11 | Volleyball Premier League using Whale Optimization Algorithm (VPLWOA) | Otsu’s thresholding | Abd Elaziz et al. (2021a) | Standard Gray Images | Proposed method is compared with SSO, FFA, WOA, VPL and SCA | PSNR, SSIM, FSIM and CPU time | The sports inspiration based on basic VPL is applied for the very first time in the field of multilevel thresholding. Experimental results confirm that the proposed algorithm outdoes other existing meta-heuristic algorithms |
| 12 | Manta Ray Foraging Optimization based on the Opposition-Based Learning (MRFO-OBL) | Otsu’s thresholding | Houssein et al. (2021b) | Computed Tomography (CT) Images: Medical Images | Proposed method is compared with SCA, MFO, EO, WOA, SSO and MRFO | PSNR and SSIM | The proposed MRFO-OBL basically finds the finest threshold values to further maximize Otsu’s function. However, in future hybridization mechanism can be tried and implemented by amalgamating proposed method with other optimization techniques |
| SL | Proposed method | Objective function | Paper details | Image type | Comparison | Quality parameters considered | Observations |
|----|-----------------|-------------------|---------------|------------|------------|-------------------------------|--------------|
| 13 | Bat Algorithm (BA) | Otsu thresholding and Kapur’s entropy | Yang et al. (2021b) | Gray scale images | Not Compared | PSNR and SSIM | The experiment results show that Otsu based method is more suitable for multi-level threshold image segmentation |
| 14 | A new entropy measure, called the t-entropy | t-entropy | Chakraborty et al. (2021) | Gray Scale Images | Proposed method is compared with k-means, W-k-means, MW-k-means, EW-k-means (Shannon) | NMI and ARI | The result shows that the proposed measure satisfies the major axiomatic properties of entropy. The application of t-entropy in the context of Power k-means clustering and sparse signal recovery is also some possible avenues for future research |
| 15 | Eagle Strategy—Whale Optimization Algorithm (ES-WOA) | Kapur’s, Fuzzy, Tsallis’, Otsu’s thresholding and Cross entropy | Ray et al. (2021) | Color Hematology Images: Medical Images | Proposed method is compared with ES-DE, ES-FA, ES-PSO and WOA | PSNR, FSIM and QILV | The proposed ES-WOA (Tsallis) acquires the best threshold values generating quicker execution times for all the images considered to be tested. However, other types of medical images namely histology, MRI, CT, Mammogram could be used with the proposed method |
| 16 | Multilevel Thresholding Based on Fuzzy-Masi Entropy | Fuzzy-Masi entropy | He et al. (2021) | Standard Color Images | Proposed method is compared with Masi and Tsalli’s entropy | PSNR, FSIM and SSIM | The results illustrate that fuzzy Masi entropy displays advanced quality and performance than other objective functions considered under the banner |
| 17 | Fuzzy Entropy Type II (FE-TII) combined with Marine Predators Algorithm (MPA) (FE-TII-MPA) | Type-II Fuzzy Entropy | Mahajan et al. (2021) | Standard Gray Scale Images | Proposed method is compared with PFA, PPA, DE, PSO and HPFPFA-D | PSNR, SSIM and MSE | Results achieved by FE-TII-MPA are comparatively better than other algorithms taken into consideration for the purpose of comparison |
| SL | Proposed method                                      | Objective function | Paper details | Image type            | Comparison | Quality parameters considered | Observations                                                                 |
|----|------------------------------------------------------|---------------------|---------------|-----------------------|------------|------------------------------|-----------------------------------------------------------------------------|
| 18 | Leader Harris Hawks Optimization (LHHO)             | Masi entropy        | Naik et al. (2021) | Standard Gray Scale Images | Proposed method is compared with HHO, CS, PSO, FA, WDO, STOA and DE | PSNR, FSIM and SSIM | The proposed LHHO rapidly attains the optimum threshold values in regard to the iteration count |
| 19 | Attacking Manta Ray Foraging Optimization (AMRFO)    | Maximum 3D Tsallis entropy | Jena et al. (2021) | MRI Images: Medical Images | Proposed method is compared with MRFO, EO, HHO, SFO, GWO, PSO and DE | PSNR, FSIM and SSIM | The proposed AMRFO produces better output in terms of quality as the 3D creation of histogram holds extra information of edge |
| 20 | Improved Particle Swarm Optimization (PSO)           | Maximum Shannon Entropy | Gong et al. (2020) | Infrared Images        | Proposed method is compared with standard PSO | SSIM and running time indicators | The experimental outcome projects that the improved PSO based total entropy image segmentation is difficult to descent towards local optimum, has greater efficiency and is reliable |
| 21 | Firefly Algorithm (FA) with levy flight and local search method | Kapur and Tsallis entropy | Sharma et al. (2020) | Standard Gray Scale Images | Kapur’s entropy and Tsallis entropy methods using improved FA algorithm are compared | PSNR and SSIM | Tsallis entropy is robust method then other method with a great standard deviation value. The proposed method may be in future used efficiently for other variants of noisy image |
| 22 | The proposed improved Teaching–Learning-based Optimization Algorithm (DI-TLBO) | Otsu’s thresholding and Kapur’s entropy | Wu et al. (2020) | Standard Gray Scale Images and X-Ray Images | Proposed method is compared with variants of DI-TLBO, TLBO, LETLBO, ITLBO, BSA and GWO | Mean fitness, standard deviation, CPU time, and MSSIM | The proposed DI-TLBO accomplishes healthier output when compared with other algorithms in terms of solution precision, and stability making the method promising in the respective field |
| SL | Proposed method                                                                 | Objective function                | Paper details | Image type          | Comparison                                      | Quality parameters considered | Observations                                                                                                                                                                                                 |
|----|---------------------------------------------------------------------------------|-----------------------------------|---------------|---------------------|------------------------------------------------|--------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 23 | The proposed Improved Lion Swarm Optimization (ILSO) algorithm; For global search and revise the updating function of LSO algorithm to improve the global and local search performance, Artificial Bee Colony optimization (ABC) is employed | Maximum Interclass Variance (Otsu's thresholding) | Li and Jiang (2020) | Standard Gray Scale Images | Proposed method is compared with PSO, ABC and LSO | PSNR                          | The proposed ILSO algorithm has better performance of global and local in terms of searching (both global and local) than the original LSO. Compared with PSO, ABC and LSO algorithm, ILSO has better convergence speed and optimization accuracy. Although the calculation speed is improved compared with the original LSO algorithm, there is still a certain gap with PSO and ABC algorithm |
| 24 | Locust Search (LS) with $J^{\text{New}}$ as objective function in Gaussian mixture model, $J^{\text{New}} + \text{LS}$ | Gaussian Mixture Model            | Cuevas et al. (2020) | Standard Gray Scale Images | Proposed method is compared with $J + \text{ABC}$, $J + \text{AIS}$ and $J + \text{DE}$ | Convergence, Accuracy and Computational Cost | The proposed $J^{\text{New}} + \text{LS}$ method removes the flaws encountered in preceding numerous evolutionary approaches |
| 25 | The proposed Improved Moth-Flame Algorithm by hybridizing Lévy flight and logarithmic function | Minimum Cross Entropy (MCE)       | Nguyen et al. (2020) | Standard Gray and Color Images | Proposed method is compared with MFO, GWO, PSO, CS, DE, PPSO, variants of MFO such as EMFO and CMFO | MSE, PSNR, FSIM and ERC        | The proposed algorithm adjust the flame-update positioning mode based on hybridizing the Lévy flight, adding inertia weight, and polynomial iteration feature to increase efficiency and produces better performance than the different competing algorithms |
| SL | Proposed method | Objective function | Paper details | Image type | Comparison | Quality parameters considered | Observations |
|----|----------------|-------------------|--------------|------------|------------|-------------------------------|--------------|
| 26 | The proposed Optimized window based combined entropy segmentation using Genetic Algorithm | Tsallis and Renyi’s entropy | Sahoo et al. (2020) | Gray Scale Images | Proposed method is compared with segmentation using Otsu’s, Tsallis and Renyi’s Entropy | ME, Precision and Recall | The proposed method works well on different images and gives comparatively promising results. The model can be further extended to adaptive window based combined entropy segmentation where number and size of the windows selected on the joint histogram can be made adaptive. |
| 27 | An Improved Emperor Penguin Optimization (IEPO) | Kapur’s entropy | Xing (2020) | Standard Color Images and Satellite Images | Proposed method is compared with EPO, WOA and MVO | PSNR, FSIM and CPU Time | The proposed IEPO reveals the authoritative and controlling skill of Kapur entropy-based algorithm. In addition, IEPO may be extended in future to solve discrete and multi-objective optimization problems. |
| 28 | Modified Thermal Exchange Optimization (Tsallis-LTEO) | Tsallis entropy | Xing and Jia (2020a) | Standard Color Images and Satellite Images | Proposed method is compared with TEO, CSA, FPA, BA and PSO | PSNR and FSIM | The proposed Tsallis-LTEO consumes less iteration but greater accuracy in terms of segmentation. |
| 29 | Teaching Tactics for Image Segmentation based on TLBO | Minimum Cross Entropy (MCE) and Otsu’s thresholding | Kalyani et al. (2020) | Berkeley Standard Color Images | Proposed method is compared with CS at 4, 5, 6, and 7 threshold levels | Mean fitness values | Experimental results authenticate that TLBO based MLT outperforms CS and reveals optimal output of TLBO is more successful in precise image segmentation and aids in various real-time applications. Otsu based TLBO is better compared to MCE. |
| SL  | Proposed method                                      | Objective function                                      | Paper details   | Image type                  | Comparison                                      | Quality parameters considered                         | Observations                                                                                                                                 |
|-----|------------------------------------------------------|--------------------------------------------------------|----------------|-----------------------------|------------------------------------------------|------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------|
| 30  | Hybrid Rice Optimization (HRO)                       | Otsu’s thresholding and Renyi’s entropy                 | Liu et al. (2020a) | Standard Gray Scale Images  | Proposed method is compared with GA, PSO, DE, ALO, ABC, WOA and SSA | PSNR, FSIM and Average Fitness values                | HRO-Renyi achieves better performance in comparison to that of HRO-Otsu. Further, HRO algorithm. May be combined with another local search mechanism and existing chaotic strategy |
| 31  | Chaotic Lightning Attachment Procedure Optimization (CLAPO) | 2D Maximum entropy                                     | Liu et al. (2020b) | Standard Gray Scale Images  | Proposed method is compared with ALO, GOA, SCA, WOA, LAPO, FWA and GA | CPU Time, Maximum fitness value, Average fitness value, Excellent Rate and Iterations consumed | The proposed CLAPO claims better outcome when compared to the other algorithms in terms of efficiency, performance and segmentation effect. However, compared to GA, SCA proposed algorithm is slower in terms of running speed that needs further attention and improvisation |
| 32  | Improved Thermal Exchange Optimization based GLCM (GLCM-ITEO) | Diagonal Class Entropy (DCE) and Otsu thresholding      | Xing and Jia (2019) | Color Natural Images, Satellite Images and Berkeley Images | Proposed method is compared with GLCM-PSO, GLCM-BASE, GLCM-FPA, GLCM-ITEO, GLCM-CSA, Otsu-CSA, Otsu-BA, Otsu-FPA, Otsu-ITEO and Otsu-PSO | PRI, VoI, GCE, CPU Time and BDE                    | The proposed GLCM-ITEO algorithm is better in terms of segmentation ability and CPU time. Further, GLCM-ITEO algorithm outperforms Otsu algorithm in terms of segmentation effect |
| 33  | Improved Cuckoo Search                               | Otsu’s thresholding                                     | Jayaseeli and Malathi (2020) | Satellite Images            | Proposed method is compared with Gaussian Smoothing method, Symmetry duality, GA based method and Lambda method | Overall Accuracy, Kappa coefficient, Commission Error and Omission Error | The resultant factors show high accuracy when compared with other existing methodologies for efficient road region extraction. The proposed method can be extended with other local search techniques of heuristic methods for improving the accuracy of road region extraction |
| SL  | Proposed method                                   | Objective function          | Paper details           | Image type                                      | Comparison                                                                 | Quality parameters considered | Observations                                                                                                                                 |
|-----|---------------------------------------------------|------------------------------|-------------------------|-----------------------------------------------|----------------------------------------------------------------------------|-------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------|
| 34  | Improved Bloch Quantum Artificial Bee Colony Algorithm (IBQABC) | Kapur’s entropy              | Hao et al. (2020)       | Standard Gray Scale Images                    | Proposed method is compared with GA, PSO and ABC                           | PSNR and FSIM                 | The proposed IBQABC is comparatively better and superior in terms of its overall performance, segmentation effect and strong generalization ability, when compared to aforementioned algorithms |
| 35  | Modified Moth-Flame Optimization Algorithm (MMFO) | Minimum Cross Entropy        | Khairuzzaman and Chaudhury (2020) | Standard Gray Scale Images                    | Proposed method is compared with PSO, MFO, BFO and WOA                   | MSSIM                         | The proposed MMFO is far better than the traditional MFO when considered for higher number of thresholds thereby drastically reducing the computation cost. In future, MMFO can be used along other entropy mechanism and also hybridized with other algorithms to solve the same |
| 36  | Minimum Cross-Entropy Self Adaptive Differential Evolution (MCE-SADE) | Minimum Cross-Entropy        | Aranguren et al. (2021) | Magnetic Resonance Brain images (MRBI): Medical Images | Proposed method is compared with SADE, GWO and ICA                      | PSNR, FSIM and SSIM           | The proposed MCE-SADE is better in terms of consistency and its quality when compared to GWO and ICA |
| 37  | Fuzzy-Entropy and Image Fusion Based method       | Fuzzy-Entropy                | Singh et al. (2020)     | Magnetic Resonance Brain images (MRBI): Medical Images | Proposed method is compared with multilevel, adaptive threshold method, K-means clustering algorithm and fuzzy c-means algorithm | PSNR and JSC                  | The proposed method outdoes the existing method. However, method is checked using only MRIs of brain tumors and in future it can be applied to other types of MRIs |
| 38  | Hybrid Slime Mould Algorithm with Whale Optimization Algorithm (HSMA_WOA) | Kapur’s entropy              | Abdel-Basset et al. (2020a) | X-Ray Images                                  | Proposed method is compared with LShade, WOA, FFA, HHA, SSA, and SMA | PSNR, SSIM, Fitness values, CPU time and UQI     | The proposed HSMA_WOA outperforms SMA for all the metrics used                                                                                                                                 |
| SL | Proposed method                                      | Objective function | Paper details          | Image type       | Comparison | Quality parameters considered | Observations                                                                 |
|----|-----------------------------------------------------|--------------------|------------------------|------------------|------------|-------------------------------|------------------------------------------------------------------------------|
| 39 | Study on recent Nature-Inspired Algorithms          | Tsallis entropy    | Wachs-Lopes et al. (2020) | Medical Images   | Proposed method is compared with FFA, CSL, GOA, KHA, GWO, EHO and WOA | PSNR, J Index, and DC | Experimental findings projects that all algorithms taken in account in the study performs likewise when quality of segmentations is the factor taken into consideration. Nevertheless, KHA generates worst results. The GWO and WOA show fastest performance with respect to time taken |
| 40 | Hybrid meta-heuristics algorithms                   | Rényi entropy      | Oliva et al. (2020)    | Color Natural Images and Berkeley Images | PSO, SCA and 2DNLMeKGSA | PSNR, SSIM and FSIM | The solution of higher quality in some of the considered images is generated by 2DNLMSCA. On the other hand, 2DNLMPSO exhibits better results for other images taken into account if focused on objective and subjective analysis of the method |
| 41 | Survey based on meta-heuristics optimization algorithms | Different objective functions ranging from Rényi entropy to Otsu’s to Kapur to Tsallis to Minimum cross-entropy to Between Class Variance, MCE, GLCM etc | Pare et al. (2020) | General Purpose and Satellite Images | PSO, QPSO, GA, DE, DE, SA, Tabu search, HBMO, BFO, MBFO, ABFO, FA, HSO, IQGA, FODPSO, MKTOA, EMO, Fuzzy c-means, QACO, CS-McCulloch, CS-Levy flight, CS-Mantegna, Darwinian PSO, CS-ELR, FPA, SSO, BA, PLBA, and BSA | MSE, PSNR, SSIM, FSIM and CPU time | The survey paper concludes based on the analysis of different algorithms that no algorithm can be considered good for all types of images neither all algorithms can be employed for specific category of image |
| SL | Proposed method | Objective function | Paper details | Image type | Comparison | Quality parameters considered | Observations |
|----|----------------|--------------------|---------------|------------|------------|-------------------------------|--------------|
| 42 | Improved Equilibrium Optimization Algorithm (EOA) | Kapur Entropy | Abdel-Basset et al. (2021a) | Standard Gray Scale Images | Proposed method is compared with WOA, BA, SCA, SSA, HHA, CSA and PSO | PSNR, MAE, SSIM, SNR and Average of the fitness function | The proposed EOA seems to lag behind other algorithms in terms of standard deviation values and CPU time however it performs superiorly when parameters such as PSNR, fitness values, SSIM, MAE and SNR |
| 43 | Non-revisiting Quantum behaved Particle Swarm Optimization (NtQPSO) | Kapur’s entropy | Yang and Wu (2020) | Standard Gray Scale Images | Proposed method is compared with CQPSO, MABC, GWO and MFO | PSNR, Accuracy, Stability, CPU Time and Computation Efficiency | The proposed NtQPSO can outperform the other state-of-the-art algorithms in regard to various performance parameters such as efficiency, effectiveness and robustness making NtQPSO suitable for real-time massive image processing |
| 44 | Hyper-Heuristic Best (HHB) and Hyper-heuristic Union Best (HHUB) | Otsu’s and Kapur’s entropy | Abd Elaziz et al. (2020) | Standard Gray Scale Images | Proposed method is compared with SCA, ABC, SSO, FASSO, FAABC and ABCSCA | SSIM, PSNR, RMSE, CPU Time and Fitness values | The proposed method obtains greater performance making it best suitable for applications related to Feature selection, multi-objective method, Global optimization, and Cloud Computing |
| 45 | Survey on Artificial Bee Colony (ABC) based classification, clustering, enhancement and segmentation | Fuzzy C-partition entropy, Otsu thresholding, Kapur’s maximum entropy, wavelet entropy | Öztürk et al. (2020) | Medical Images, Satellite Images, Standard Gray Scale Images | Classification: ABC with PSO and GA. Further, ABC-SVM with PSO-SVM and GA-SVM Clustering: ABC with PSO, GA and K-Means, FCM, PSO-FCM, ABC-FCM, MABC-FCM and MoABC-FCM. Segmentation: I-ABC, ABC, GA, AFS, PSO, DE and ABC | Xie-beni index, Partition coefficient, Classification entropy, separateness, compactness, Davies–Bould in Index, and XB Index | The analysis performed while surveying highlights that for classification, segmentation, clustering, and enhancement of medical images, ABC algorithm gives fruitful and promising result |
| SL | Proposed method | Objective function | Paper details | Image type | Comparison | Quality parameters considered | Observations |
|----|----------------|-------------------|---------------|------------|------------|-------------------------------|--------------|
| 46 | Method using multi-level thresholding algorithm and Statistical Region Merging (SRM) technique with the help of the Alternating Direction Method of Multipliers (ADMM) and MEC | Minimum Cross Entropy | Li et al. (2019) | Standard Color Images | Proposed method is compared with PSO, BF, DE and CS | PSNR, FSIM and SSIM | The proposed ADMM shows some better properties such as faster calculation speed (the request time was under 0.1 s) and better stability |
| 47 | Crow Search Algorithm (CSA) | Kapur’s entropy | Upadhyay and Chhabra (2020) | Standard Gray Scale Images | Proposed method is compared with PSO, DE, GWO, MFO and CS | PSNR, FSIM and SSIM | The proposed CSA showcase high robustness, accuracy, efficiency, suitability and search capability when compared with other mentioned algorithms. Further, proposed method could be suitable to be applied over multispectral satellite images and moreover to focus on multi-objective optimization problems |
| 48 | Whale Optimization Algorithm (WOA) | Kapur’s entropy | Yan et al. (2020) | Gray Scale Images | Proposed method is compared with BA, FPA, MFO, MSA, PSO and WWO | The fitness value, PSNR, SSIM and execution time | The proposed WOA has the ability to explore and further navigate between the global and local search with the sole intention to obtain the optimum solution to the given problem. Further, the same is projected using the experimental results showing its better performance in terms of convergence speed and quality of segmentation |
Table 3 (continued)

| SL  | Proposed method                          | Objective function       | Paper details      | Image type | Comparison                                                                 | Quality parameters considered | Observations                                                                 |
|-----|-----------------------------------------|--------------------------|--------------------|------------|-----------------------------------------------------------------------------|-------------------------------|------------------------------------------------------------------------------|
| 49  | Bat Algorithm (BA1)                     | Kapur’s entropy          | Dey et al. (2021)  | Standard Color and Gray Scale Images | Proposed method is compared with BA2, BA3, BA4 and BA5                   | PSNR, NCC, AD, SC and NAE     | Though the average IQPs attained using all BA methods are identical. However, the Levy-based BA presents better results when compared to other algorithms in terms of its convergence speed. |
| 50  | Kapur’s entropy-based thresholding method| Kapur’s entropy          | Aalan Babu et al. (2020) | Satellite Images | Proposed method is compared with Otsu, Tsallis entropy and Fuzzy entropy | Precision, Recall, F-measure, Specificity, Overall Accuracy, SSIM and MAD | The proposed method yields better segmentation with an overall accuracy of 98.43% and SSIM rate of 0.9712. |
| 51  | Stochastic Fractal Search (SFS)          | Fuzzy Entropy            | Dhal et al. (2019b) | Satellite Images | Proposed method is compared with PSO, CS, HSO and ABC                      | PSNR, FSIM, QILV              | The proposed SFS produces utmost satisfactory results in a shorter computational time. |
| 52  | Modified Salp Swarm Algorithm (MSSA)    | Otsu’s thresholding, Kapur’s and Renyi entropy | Wang et al. (2020) | Standard Color Images | Proposed method is compared with SSA, WOA and FPA using different entropy such as Kapur’s, Otsu and Renyi entropy | Best Fitness values, PSNR, FSIM, PRI, Vol, GCE and BDE | The proposed MSSA is superior to Kapur’s entropy segmentation algorithm yielding PSNR and SSIM value superior as compared to other algorithms. |
| 53  | Renyi Electromagnetism Mechanism Optimisation (R-EMO) | Renyi’s, Tsallis and Kapur’s entropy | Bhandari et al. (2019) | Various Satellite and Standard Color Images | Proposed method is compared with BA, BSA, FA, PSO and WDO using Renyi, Tsallis and Kapur’s entropy | ME, MSE, PSNR, FSIM, SSIM and Entropy | The proposed EMO-Renyi’s outperforms other algorithm when applied with each of the objective function. The proposed scheme in future may be extended for medical image segmentation due to its rapid segmentation capability. |
| SL | Proposed method | Objective function | Paper details | Image type | Comparison | Quality parameters considered | Observations |
|----|-----------------|--------------------|---------------|------------|------------|-------------------------------|--------------|
| 54 | Improved Particle Swarm Optimization (IPSO) algorithm aided with fuzzy-entropy, IPSO-Fuzzy. Output of IPSO-fuzzy is used to train SVM classifier | Fuzzy entropy | Chakraborty et al. (2019a) | Various Satellite and Standard Color Images | Proposed method is compared with CS, DE, FF, GA and PSO | PSNR, FSIM, Overall Accuracy, Kappa Index, Mean Accuracy and IoU | The proposed IPSO doesn't prematurely converge and in future may be applied on some larger dataset like ImageNet, COCO with respect to object recognition |
| 55 | Improved Elephant Herding Optimization (IEHO) | Kapur’s entropy and between-class variance (Otsu's thresholding) | Chakraborty et al. (2019b) | Standard Gray Scale Images | Proposed method is compared with CS, ABC, BA, PSO, EHO and DP | PSNR, FSIM and SSIM | The proposed IEHO performs better than that of the conventional algorithms both in terms of quality and convergence rate |
| 56 | Whale Optimization Algorithm-Differential Evolution (WOA-DE) | Kapur’s entropy | Lang and Jia (2019) | MRI: Medical Images, Satellite Images, standard gray scale Images | Proposed method is compared with WOA, SSA, SCA, ALO, HSO, BA, PSO, BDE and IDSA. Otsu WOA-DE is compared with Kapur WOA-DE | Average Fitness Values, PSNR, FSIM and SSIM | The proposed WOA-DE avoids the loss due to population diversity and dropping into local optimum. Kapur_WOA-DE is better than Otsu_WOA-DE as per the experimental outcome analysis. |
| 57 | Spherical Search Optimizer and Sine Cosine Algorithm (SSOSCA) | Fuzzy Entropy | NajiAlwerfali et al. (2020) | Standard Gray scale Images | Proposed method is compared with CS, GWO, WOA, SSA, GOA and SSO. Optimizer (SSO) | Fitness value, PSNR and SSIM | The proposed SSO-SCA in terms of fitness value, PSNR and SSIM is better than other algorithms take into consideration for comparison purpose. In future, for time series forecasting, cloud computing, feature selection etc., proposed method may be effective |
| SL | Proposed method | Objective function | Paper details | Image type | Comparison | Quality parameters considered | Observations |
|----|----------------|--------------------|---------------|------------|------------|-------------------------------|--------------|
| 58 | Differential Evolution and Whale Optimization (DEWO) | Non-local 2-dimensional histogram-based Entropy | Vig et al. (2019) | Standard color Images | Proposed method is compared with DE, ABC, CS and WOA. Different entropy functions such as Tsallis, Renyi and Kapur was compared | Mean fitness and number of function evaluation | The proposed DEWO offer a healthier stability amongst exploration and exploitation. The experimental result showcases that which so ever entropy function selected, proposed algorithm is able to attain maximized value of fitness function |
| 59 | Improved Particle Swarm Optimization (PSO) | Otsu's thresholding | Khairuzaman and Chaudhury (2019) | Brain MRI: Medical Images | Proposed method is compared with standard PSO and BFO | PSNR and MSSIM | The proposed method suggestively provides improved quality in terms of image segmentation which when applied to T2-weighted brain MR images |
| 60 | Fractional Order Darwinian Particle Swarm Optimization (FODPSO) | Otsu's thresholding | Astuti and Mardhia (2019) | Hyper spectral Images: Standard Color Images | Proposed method is compared with PSO and DPSO | Average CPU time, fitness value, PSNR, MSE and SSIM | The proposed FODPSO in the context of fitness value and processing time of CPU is better compared to the other algorithms considered |
| 61 | Teaching–Learning Optimization based Minimum Cross Entropy Thresholding (TLBO-MCET) | Minimum Cross entropy | Gill et al. (2019) | Standard Gray Scale Images | Proposed method is compared with FF- MCET), HBMO-MCET) and (QPSO-MCET) | Uniformity, Fitness values and PSNR | The proposed TLBO-MCET is considered to be an efficient method to determine optimal threshold values. TLBO-MCET has great potential in the field of image segmentation |
| SL | Proposed method                                                                 | Objective function | Paper details                        | Image type           | Comparison                                                                                                                                  | Quality parameters considered | Observations                                                                                                                                 |
|----|---------------------------------------------------------------------------------|--------------------|--------------------------------------|----------------------|------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------|
| 62 | Energy 3D Otsu Human Learning Optimization (HLO) (E-3D-HLO)                     | 3D Otsu’s, Energy-Otsu thresholding | Bhandari and Kumar (2019)             | Standard Color Images | Proposed method is compared to SCA, CFA, HLO, E-SCA and E-HLO. Also, E-3D-HLO is then compared to 1D, 2D and 3D-SCA, CFA and HLO | ME, MSE, PSNR, FSIM, SSIM and Entropy | Otsu in three-dimensional space possesses the ability to incorporate spatial context information making it better when compared with 1D and 2D Otsu methods. The segmentation accuracy upsurges significantly without distressing the original color image details making the proposed method better than the other algorithms used for the purpose of comparison |
| 63 | Improved Opposition based Symbiotic Organisms Search (IOSOS)                     | Otsu’s thresholding, Kapur’s and Tsallis entropy | Chakraborty et al. (2019c)           | Standard Color Images | Proposed method is compared to OSOS, CS, BA, ABC and PSO                                                                                     | PSNR, FSIM and SSIM            | The proposed IOSOS employing various entropy functions such as Otsu, Tsallis and Kapur performs significantly when compared with the different algorithms used for the purpose of comparison |
| 64 | Hybrid Adaptive-Cooperative Learning strategy with Fruit Fly Optimization Algorithm (FOA) (HACLFOA) | Otsu’s thresholding | Ding et al., (2019)                  | Standard Gray and Color Images | Proposed method is compared to FOA, LGMS-FOA, IFFO, CMFOA and SFOA. Further, HACLFOA is compared with PSO, FOA, QPSO and IDPSO | Fitness values and Computation time | The proposed HACLFOA has strongest global convergence ability among the compared algorithms thereby have a great potential in the image processing field |
| 65 | Thresholding Heuristic (TH) embedded into WOA, GWO and PSO (WOA-TH, GWO-TH, and PSO-TH) | Otsu’s thresholding | Bohat and Arya (2019)                | Standard Gray Scale Images | Proposed method is compared with their respective base algorithm WOA, GWO and PSO                                                          | Mean Fitness values, MSSIM and Mean Execution Time | The proposed WOA-TH, GWO-TH and PSO-TH algorithms are better with improved computational time when compared with their respective base algorithm |
| SL | Proposed method                                                                 | Objective function | Paper details | Image type              | Comparison | Quality parameters considered | Observations                                                                 |
|----|--------------------------------------------------------------------------------|--------------------|--------------|-------------------------|------------|-------------------------------|----------------------------------------------------------------------------|
| 66 | Adaptive Differential Evolution with Levy Distribution (ALDE)                    | Otsu’s thresholding | Tarkhaneh and Shen (2019) | MRI: Medical Images     | Proposed method is compared with SDE, BDE and hjDE | PSNR and SSIM | The proposed ALDE when equated with the benchmark algorithm performs better and has the capability to attain optimal threshold at a judicious computational cost |
| 67 | Sigmoid based optimal threshold selection technique with Differential Evolution (DE) and Tsallis Fuzzy | Tsallis-Fuzzy Entropy | Raj et al. (2019) | Standard Color Images | Proposed method is compared with PLBA, BFO, MBFO and BA | PSNR, SSIM, SNR and CPU time | The proposed method is more stable and converges to optimal thresholds much faster. Standard deviation values further suggest that the proposed method is highly robust when compared with other algorithms |
| 68 | Energy-Masi using Moth Swarm Algorithm (MASI-ENG-MSA)                           | Energy-Masi entropy | Bhandari and Rahul (2019) | Standard Color Images | Proposed method is compared with MASI-DA, MASI-SCA, MASI-WOA, MASI-GOA, MASI-MSA, MASI-ENG-DA, MASI-ENG-SCA, MASI-ENG-WOA and MASI-ENG-GOA | ME, Entropy, MSE, PSNR, SSIM and FSIM | The proposed MASI-ENG-MSA in regard to the parameters such as threshold quality and computational cost outperforms other algorithms |
| 69 | Particle Swarm Optimization. Using Gray Level &Local-Average histogram (GLLA) and Tsallis-Havrda-Charv’at entropy | Tsallis-Havrda-Charv’at entropy | Borjigin and Sahoo (2019) | Standard Color Images | The average of PRI, GCE, VOI and BDE of proposed model is compared with result from 2D K-L divergence model, 1D Tsallis-based model and 2D Renyi-based model | VOL, GCE, BDE and PRI | The experiments have been extensively conducted and highlight the effectiveness and reasonability of the proposed method |
| SL | Proposed method | Objective function | Paper details | Image type | Comparison | Quality parameters considered | Observations |
|----|----------------|-------------------|---------------|------------|------------|-------------------------------|--------------|
| 70 | Masi-Water Cycle Algorithm (M-WCA) | Tsallis and Masi entropy | Kandhway and Bhandari (2019a) | Standard Color Images | Proposed method is compared with BA, PSO, WDO, MBO, GOA, and WCA. Further, Masi-BAT, Masi-PSO, Masi-WDO, Masi-MBO, Masi-GOA, and Masi-WCA, Tsallis-BAT, Tsallis-PSO, Tsallis-WDO, Tsallis-MBO, Tsallis-GOA, and Tsallis-WCA comparison is also highlighted | ME, MSE, PSNR, FSIM, SSIM, computational time and Entropy | The proposed Masi-WCA is capable of acquiring superior quality and convergence rate. The foremost constraint of M-WCA method is that it consumes long processing time for segmentation compared to Masi-MBO. However, when different optimization methods are coupled with Masi entropy always performs better than the Tsallis entropy-based optimization techniques |
| 71 | Multi-Verse Optimizer (MVO) | Energy-Minimum Cross Entropy (MCE) | Kandhway and Bhandari (2019b) | Standard Color Images | Proposed method is compared to BA, MFO, AGPSO, TSA and MVO | ME, MSE, PSNR, SSIM, FSIM and GMSD | The proposed MVO-Energy-MCE when compared to other mentioned algorithm performs much better in terms of segmented performance and thresholding making it efficient, robust and accurate algorithm |
| 72 | Optimized Thresholding Method Using Ant Colony Algorithm | Otsu's thresholding | Khorram and Yazdi (2019) | Magnetic Resonance (MR) Brain Images: Medical Images | Proposed method is compared with PSO, ABC, K-means, and EM | Accuracy, Sensitivity, Specificity, FDR, PPV, FOR and NPV | The experimental outcomes prove the promising result of the proposed method when compared to other algorithms. In future, the proposed approach may be further prolonged over 3D MR brain images |
| SL | Proposed method | Objective function | Paper details | Image type | Comparison | Quality parameters considered | Observations |
|----|-----------------|--------------------|---------------|------------|------------|-------------------------------|--------------|
| 73 | Salp Swarm Algorithm using Levy Flight (LSSA) to GLCM (GLCM-LSSA) | Diagonal Class Entropy (DCE) | Xing and Jia (2020b) | Standard Color Images and Satellite Images | Proposed method is compared to WOA, SSA, FPA, PSO and BA. Further, GLCM-LSSA is compared GLCM-PSO, GLCM-BA, GLCM-FPA, Kapur-LSSA, Kapur-WOA, Kapur-FPA, Kapur-PSO and Kapur-BA | PSNR, FSIM, PRI, BDE, GCE, Vol and Computation Time | The proposed GLCM-LSSA algorithm has the capability to handle complex segmentation procedures as it possesses better segmentation effect. |
| 74 | Self-Adaptive Moth-Flame Optimization Thresholding Heuristic (SAMFO-TH) | Otsu’s thresholding and Kapur’s entropy | Jia et al. (2019a) | Standard Color Images | Proposed method is compared with MVO, WOA, FPA, SCA, ACO and MFO | Computational time, MVTR, MSE, PSNR, SSIM, FSIM, PRI, Vol and TVD | The proposed SAMFO-TH is superior in terms of stability, convergence rate, accuracy and efficiency. Kapur-SAMFOTH outdoes Otsu’s-SAMFOTH; SAMFOTH outperforms MFO which is clearly highlighted in the experimental result. |
| 75 | Multi-Strategy Emperor Penguin Optimizer (MSEPO) | Masi Entropy | Jia et al. (2019b) | Color Satellite Images | Proposed method is compared with FPA, CSA, TLBO, MABC, IDS, LMVO, and EPO | PSNR, SSIM, FSIM and Computational time | The proposed MSEPO is capable of effectively identifying the core target areas and process its edges better. The binary and multi-objective versions of MSEPO algorithm may be developed in future to explore the capabilities of MSPO in a broader way. |
| 76 | Cuckoo Search (CS) | Tsallis entropy | Widyantara et al. (2019) | Coastal video Images | – | PSNR, SSIM and FSIM | The amalgamation of CS algorithms along with Tsallis functions furnished better outcomes than that of conventional segmentation methods. |
| SL | Proposed method | Objective function | Paper details | Image type | Comparison | Quality parameters considered | Observations |
|----|----------------|--------------------|---------------|------------|------------|-----------------------------|--------------|
| 77 | Modified Grasshopper Optimization Algorithm (MGOA) | Energy-Tsallis entropy | Liang et al. (2019) | Standard Color Images | Proposed method is compared with GOA, WOA, FPA, PSO and BA | PSNR and SSIM | The proposed MGOA using energy based Tsallis entropy when certain performance parameters (accuracy, convergence speed, searching precision) are considered generates superior performance. Similarly, WOA and BA achieves acceptable outcome however, PSO generates substandard performance |
| 78 | Multi-objective Multi-universe Optimization (MOMVO) | Otsu’s thresholding and Kapur’s entropy | Abd Elaziz et al. (2019a) | Standard Gray Scale Images | Proposed method is compared with MOPSO, MOEAD and MOEADR | HV, SP and U | The proposed MOMVO is substantially better compared to the other algorithms in terms of hyper volume and spacing |
| 79 | Knee Evolutionary Algorithm (KnEA) | Kapur, Otsu, cross entropy, Tsalli’s entropy, Renyi entropy, fuzzy entropy | Abd Elaziz and Lu (2019) | Standard Gray Scale Images | Proposed method is compared with NSGA-III, RVEA and IMMOEA and LMEA | PSNR, SSIM and Computational Time | The proposed KnEA method produced a high-quality segmented image at different levels of threshold. In addition, the CPU time(s) achieved by the KnEA is lower than the CPU time(s) of others, except the RVEA, and IMMOEA methods |
| 80 | Swarm Selection (SS) | Otsu’s thresholding | Abd Elaziz et al. (2019b) | Standard Gray Scale Images | Proposed method is compared with ABCSCA, ABC, FAABC, FASSO and SCA | PSNR, FSIM, SSIM and Computational Time | The proposed SS method outperforms the other algorithms at most of the threshold levels along each image, based on different performance measures |
| SL | Proposed method                                                                 | Objective function | Paper details     | Image type                | Comparison                                                                 | Quality parameters considered                                                                 | Observations                                                                                                                                                                                                 |
|----|---------------------------------------------------------------------------------|--------------------|-------------------|--------------------------|----------------------------------------------------------------------------|---------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 81 | Hybrid Bird Mating Optimization and Differential Evolutionary (BMO-DE)          | Otsu’s thresholding, and Kapur’s entropy | Ahmadi et al. (2019) | Standard Gray Scale Images | Proposed method is compared with BF, MBE, PSO, GA and PSO-DE | Fitness function value, average CPU running time and SNR | The proposed BMO-DE with respect to parameters such as solution quality and stability is better than the subsequent algorithms employed for the sole purpose of comparison. In future, objective function may be integrated to the spatial constraints to improve the accuracy. |
| 82 | Tournament based Lévy Multi-Verse Optimization (TLMVO)                          | Masi entropy       | Jia et al. (2019c) | Standard Color Images    | Proposed method is compared with MVO, LMVO, ALO, DA, FPA, PSO and CS      | Fitness function value, average CPU running time, PSNR, SSIM and FSIM                         | The proposed TLMVO proved its significance in high-dimensional optimization problems, thereby generating good objective function value, image quality, convergence performance and robustness.                                                                                     |
| 83 | GOA with self-adaptive Differential Evolution (GOA-jDE)                        | Minimum Cross Entropy (MCE) | Jia et al. (2019d) | Color and Gray Scale Satellite Images | Proposed method is compared with GOA, DE, MGOA, hjDE, BA, BDE and PSO | Average Fitness Function value, PSNR, FSIM, SSIM and computation time | The proposed GOA-jDE showcases through its experimental result, its capabilities to be adopted and implemented in several areas by outperforming other approaches. In future, apart from satellite images, medical images too may be explored using the proposed method.                                         |
| 84 | Dynamic Harris Hawks Optimization with a Mutation Mechanism (DHHOM)            | Kapur’s, Tsallis entropy and Otsu thresholding | Jia et al. (2019e) | Color Satellite Images   | Proposed method is compared with HHO, TLBO, WOA-TH, IDSA and BDE DHHOM is then compared Tsallis-MGOA, Tsallis-MABC, Otsu-MFPA and Otsu-GWO | Average Fitness Function value, PSNR, SSIM and FSIM | The proposed DHHOM based thresholding technique shows remarkable performance.                                                                                                                                                                                  |
| SL | Proposed method | Objective function | Paper details | Image type | Comparison | Quality parameters considered | Observations |
|----|----------------|-------------------|---------------|------------|------------|------------------------------|--------------|
| 85 | Fractional Order Darwinian Particle Swarm Optimization (FODPSO) | Otsu’s and Kapur’s method | Ahilan et al. (2019) | Medical Images | Proposed method is compared with DPSO and PSO | Fitness Function value, PSNR and MSE | The proposed FODPSO generate superior results. The fractional coefficient in FODPSO algorithm makes it effective optimization with fast convergence rate |
| 86 | Bat Algorithm (BA) | Rényi’s entropy and Otsu’s thresholding | Pare et al. (2019) | Standard Color Images and Satellite Images | Proposed method is compared with Otsu-PSO and Renyi-PSO | PSNR, MSE and Computation Time | The proposed method is more competent and resourceful for image segmentation as compared to the different algorithm taken into account in this paper |
| 87 | Dragonfly Algorithm with Opposition-Based Learning (OBLDA) | Otsu’s thresholding and Kapur’s entropy | Bao et al. (2019) | Standard Color Images and Satellite Images | Proposed method is compared with DA, PSO, CSA, BA, HSO, ALO and SSA | Average Fitness Function value, PSNR, FSIM, SSIM and computation time | The proposed OBLDA is advantageous over the compared algorithm for segmentation because of its accuracy and notable stability |
| 88 | Improved Grey Wolf Optimization (IGWO) | Kapur’s entropy | Yao et al. (2019) | Standard Gray Scale Images | Proposed method is compared with PSO | PSNR | The proposed IGWO possesses great global convergence along with the computational robustness, thereby avoiding the fall into local optimum |
Table 4  Different method’s abbreviation used in the paper surveyed in Table 3 and its full form

| SL | Method’s name (abbreviation) | Full form |
|----|------------------------------|-----------|
| 1  | RCACO                        | Random spare strategy and Chaotic intensification strategy based on ACOR |
| 2  | ACOR                         | Ant Colony Optimizer for Continuous Domain |
| 3  | PSO                          | Particle Swarm Optimization |
| 4  | WOA                          | Whale Optimization Algorithm |
| 5  | CS                           | Cuckoo Search |
| 6  | CSL                          | Cuckoo Search via Lévy Flights |
| 7  | BA                           | Bat Algorithm |
| 8  | BLPSO                        | Biogeography-based Learning Particle Swarm Optimization |
| 9  | CGPSO                        | Cluster Guide Particle Swarm Optimization |
| 10 | IWOA                         | Improved Whale Optimization Algorithm |
| 11 | IGWO                         | Enhanced Gray Wolf Optimization |
| 12 | SSA                          | Salp Swarm Algorithm |
| 13 | CGPSO                        | Cluster Guide Particle Swarm Optimization |
| 14 | SMA                          | Slime Mould Algorithm |
| 15 | CCACO                        | Criss Cross Ant Colony Optimization |
| 16 | HCS                          | Horizontal Crossover Search |
| 17 | VCS                          | Vertical Crossover Search |
| 18 | CSO                          | Crisscross Optimizer |
| 19 | DE                           | Differential Evolution |
| 20 | WOA                          | Whale Optimizer Algorithm |
| 21 | GWO                          | Gray Wolf Optimization |
| 22 | SCA                          | Sine Cosine Algorithm |
| 23 | HHO                          | Harris Hawks Optimization |
| 24 | OBLGWO                       | Oppositional Based Grey Wolf Optimization Algorithm |
| 25 | ALCPSO                       | Particle Swarm Optimization with an Aging Leader and Challengers |
| 26 | m_SCA                        | Modified Sine Cosine Algorithm |
| 27 | BMWOA                        | Enhanced Associative Learning-based Exploratory Whale Optimization Algorithm |
| 28 | ACWOA                        | A-C parametric Whale Optimization Algorithm |
| 29 | SCADE                        | Hybridizing Sine Cosine Algorithm with Differential Evolution |
| 30 | MFO                          | Moth Flame Optimization |
| 31 | AMFO                         | Advanced variants of Moth Flame Optimization |
| 32 | FPA                          | Flower Pollination Algorithm |
| 33 | ABC                          | Artificial Bee Colony |
| 34 | MABC                         | Modified Artificial Bee Colony |
| 35 | IABC                         | Improved Artificial Bee Colony |
| 36 | FA                           | Firefly Algorithm |
| 37 | TLBO                         | Teaching–Learning-Based Optimization |
| 38 | FDRPSO                       | Fitness-Distance-Ratio-Based Particle Swarm Optimization |
| 39 | FDR-TLBO                     | Fitness-Distance-Ratio-Based Particle Swarm Optimization |
| 40 | BBPSO                        | Bare Bones Particle Swarm Optimization |
| 41 | jDE                          | j Differential Evolution |
| 42 | SADE                         | Self-Adaptive Differential Evolution |
| 43 | NFDR-TLBO                    | Neighborhood Fitness Distance Ratio-Teaching Learning Based Optimization |
| 44 | GA                           | Genetic Algorithm |
| 45 | MWOA                         | Modified Whale Optimization Algorithm |
| 46 | VPL                          | Volleyball Premier League |
| 47 | VPLWOA                       | Volleyball Premier League using Whale Optimization Algorithm |
| 48 | SSO                          | Social Spider Optimization |
| 49 | SOA                          | Seeker Optimization Algorithm |
| 50 | FFA                          | Firefly Algorithm |
| SL  | Method’s name (abbreviation) | Full form                                                                 |
|-----|------------------------------|---------------------------------------------------------------------------|
| 51  | EO                           | Equilibrium Optimization                                                  |
| 52  | SSO                          | Slap Swarm Optimization                                                   |
| 53  | MRFO                         | Manta Ray Foraging Optimization                                           |
| 54  | MRFO-OBL                     | Manta Ray Foraging Optimization based on the Opposition-Based Learning    |
| 55  | ES-WOA                       | Eagle Strategy-Whale Optimization Algorithm                              |
| 56  | ES-DA                        | Eagle Strategy-Differential Evolution                                     |
| 57  | ES-FA                        | Eagle Strategy-Firefly Algorithm                                          |
| 58  | ES-PSO                       | Eagle Strategy-Particle Swarm Optimization                               |
| 59  | MPA                          | Marine Predators Algorithm                                               |
| 60  | FE-TII-MPA                   | Fuzzy Entropy Type II-Marine Predators Algorithm                          |
| 61  | PFA                          | Paddy Field Algorithm                                                    |
| 62  | PPA                          | Plant Propagation Algorithm                                              |
| 63  | HPFPPA-D                     | Hybrid Paddy Field Plant Propagation Algorithm with the Disruption Operator|
| 64  | LHHO                         | Leader Harris Hawks Optimization                                         |
| 65  | HHO                          | Harris Hawks Optimization                                                |
| 66  | WDO                          | Wind Driven Optimization                                                 |
| 67  | STOA                         | Sooty Tern Optimization Algorithm                                        |
| 68  | AMRFPO                       | Attacking Manta Ray Foraging Optimization                                |
| 69  | SFO                          | Sail Fish Optimizer                                                      |
| 70  | HBMO                         | Honey Bee Mating Optimization                                            |
| 71  | ITLBO                        | Improved Teaching–Learning-based Optimization                            |
| 72  | BSA                          | Backtracking Search Optimization Algorithm                               |
| 73  | ILSO                         | Improved Lion Swarm Optimization                                         |
| 74  | LSO                          | Lion Swarm Optimization                                                  |
| 75  | J + ABC                      | J + Artificial Bee Colony                                                |
| 76  | J + AIS                      | J + Artificial Immune System                                             |
| 77  | J + DE                       | J + Differential Evolution                                               |
| 78  | PPSO                         | Parallel Particle Swarm Optimization                                     |
| 79  | EMFO                         | Enhanced Moth-Flame Algorithm                                            |
| 80  | CMFO                         | Chaos-enhanced Moth-Flame Algorithm                                      |
| 81  | EPO                          | Emperor Penguin Optimization                                             |
| 82  | MVO                          | Multi Verse Optimization                                                 |
| 83  | IEPO                         | Improved Emperor Penguin Optimization                                    |
| 84  | Tsallis—LTEO                 | Tsallis—Modified Thermal Exchange Optimization                            |
| 85  | TEO                          | Thermal Exchange Optimization                                            |
| 86  | CSA                          | Crow Search Algorithm                                                    |
| 87  | GA                           | Genetic Algorithm                                                       |
| 88  | ALO                          | Ant-Lion Optimization                                                    |
| 89  | LAPO                         | Lightning Attachment Procedure Optimization                              |
| 90  | CLAPO                        | Chaotic Lightning Attachment Procedure Optimization                      |
| 91  | GOA                          | Grasshopper Optimization Algorithm                                       |
| 92  | FWA                          | Fire Works Algorithm                                                     |
| 93  | GLCM-PSO                     | Gray Level Co occurrence Matrix- Particle Swarm Optimization             |
| 94  | GLCM-BA                      | Gray Level Co occurrence Matrix-Bat Algorithm                            |
| 95  | GLCM-FPA                     | Gray Level Co occurrence Matrix-Flower Pollination Algorithm             |
| 96  | GLCM-ITEO                    | Gray Level Co occurrence Matrix-Improved Thermal Exchange Optimization    |
| 97  | GLCM-CSA                     | Gray Level Co occurrence Matrix-Crow Search Algorithm                    |
| 98  | Otsu-CSA                     | Otsu-Crow Search Algorithm                                               |
| 99  | Otsu-BA                      | Otsu-Bat Algorithm                                                       |
| 100 | Otsu-FPA                     | Otsu-Flower Pollination Algorithm                                        |
Table 4 (continued)

| SL | Method’s name (abbreviation) | Full form |
|----|------------------------------|-----------|
| 101 | Otsu-PSO | Otsu-Particle Swarm Optimization |
| 102 | Otsu-ITEO | Otsu-Improved Thermal Exchange Optimization |
| 103 | MMFO | Modified Moth-Flame Optimization Algorithm |
| 104 | IBQABC | Improved Bloch Quantum Artificial Bee Colony Algorithm |
| 105 | BFO | Bacterial Foraging Optimization |
| 106 | ABFO | Adaptive Bacterial Foraging Optimization |
| 107 | MBFO | Modified Bacterial Foraging Optimization |
| 108 | MCE-SADE | Minimum Cross-Entropy-Self-Adaptive Differential Evolution |
| 109 | ICA | Competitive Imperialist Algorithm |
| 110 | KHA | Krill Herd Algorithm |
| 111 | EHO | Elephant Herding Optimization |
| 112 | PLBA | Patch Levy-based Bees Algorithm |
| 113 | EMO | Electromagnetism-like algorithm |
| 114 | MKTOA | Molecular Kinetic Theory Optimization Algorithm |
| 115 | HBMO | Honey Bee Mating Optimization |
| 116 | IQGA | Improved Quantum-inspired Genetic Algorithm |
| 117 | FODPSO | Fractional-order Darwinian Particle Swarm Optimization |
| 118 | QACO | Quantum-inspired Ant Colony Optimization |
| 119 | QDE | Quantum-inspired Differential Evolution |
| 120 | QPSO | Quantum-inspired Particle Swarm Optimization |
| 121 | QGA | Quantum-inspired Genetic Algorithm |
| 122 | BSA | Backtracking Search Algorithm |
| 123 | BA | Bee Algorithm |
| 124 | QBA | Quantum-inspired Bee Algorithm |
| 125 | HSO | Harmony Search Optimization |
| 126 | NrQPSO | Non-revisiting Quantum-behaved Particle Swarm Optimization |
| 127 | CQPSO | Chaotic Quantum-Behaved Particle Swarm Optimization |
| 128 | MABC | Modified Artificial Bee Colony |
| 129 | HHB | Hyper-Heuristic Best |
| 130 | HHUB | Hyper-heuristic Union Best |
| 131 | FASSO | Hybrid Firefly Algorithm and Social-Spider Optimization |
| 132 | FAABC | Hybrid Firefly Algorithm and Artificial Bee Colony |
| 133 | ABCSCA | Hybrid Artificial Bee Colony and Sine Cosine Algorithm |
| 134 | ABC-SVM | Artificial Bee Colony-Support Vector Machine |
| 135 | PSO-SVM | Particle Swarm Optimization-Support Vector Machine |
| 136 | GA-SVM | Genetic Algorithm-Support Vector Machine |
| 137 | PSO-FCM | Particle Swarm Optimization-Fuzzy C-Means |
| 138 | ABC-FCM | Artificial Bee Colony-Fuzzy C-Means |
| 139 | MABC-FCM | Modified Artificial Bee Colony-Fuzzy C-Means |
| 140 | MoABC-FCM | Multi-Objective Modified Artificial Bee Colony-Fuzzy C-Means |
| 141 | SFS | Stochastic Fractal Search |
| 142 | MSSA | Modified Salp Swarm Algorithm |
| 143 | WDO | Wind Driven Optimization (WDO) |
| 144 | IEHO | Improved Elephant Herding Optimization |
| 145 | BDE | Beta Differential Evolution |
| 146 | IDSAA | Improved Differential Search Algorithm |
| 147 | SSO | Spherical Search Optimizer |
| 148 | SSOSCA | Spherical Search Optimizer and Sine Cosine Algorithm |
| 149 | FODPSO | Fractional Order Darwinian Particle Swarm Optimization |
| 150 | FF-MCET | Firefly-based Minimum Cross Entropy Thresholding |
| SL | Method’s name (abbreviation) | Full form |
|----|-----------------------------|-----------|
| 151 | TLBO-MCET | Teaching–Learning based Optimization based Minimum Cross Entropy Thresholding |
| 152 | HBMO-MCET | Honey Bee Mating Optimization based Minimum Cross Entropy Thresholding |
| 153 | QPSO-MCET | Quantum Particle Swarm Optimization-based Minimum Cross Entropy Thresholding |
| 154 | OSOS | Opposition based Symbiotic Organisms Search |
| 155 | IOSOS | Improved Opposition based Symbiotic Organisms Search |
| 156 | CFA | Cuttle Fish Algorithm |
| 157 | HLO | Human Learning Optimization |
| 158 | E-SCA | Energy-Sine Cosine Algorithm |
| 159 | E-CFA | Energy-Cuttle Fish Algorithm |
| 160 | E-HLO | Energy-Human Learning Optimization |
| 161 | FOA | Fruit Fly Optimization Algorithm |
| 162 | HACLFOA | Hybrid Adaptive-Cooperative Learning strategy with Fruit Fly Optimization Algorithm |
| 163 | CMFOA | Cloud Model based Fruit Fly Optimization Algorithm |
| 164 | SFOA | Step Fruit Fly Optimization Algorithm |
| 165 | IDPSO | Particle Swarm Optimization based on Intermediate Disturbance Strategy |
| 166 | WOA-TH | Whale Optimization Algorithm-Thresholding Heuristic |
| 167 | GWO-TH | Gray Wolf Optimization-Thresholding Heuristic |
| 168 | PSO-TH | Particle Swarm Optimization-Thresholding Heuristic |
| 169 | ALDE | Adaptive Differential Evolution with Levy Distribution |
| 170 | SDE | Synergetic Differential Evolution |
| 171 | hjDE | Hybrid Differential Evolution |
| 172 | MSA | Moth Swarm Algorithm |
| 173 | MASI-ENG-MSA | Energy-Masi Moth Swarm Algorithm |
| 174 | MASI-DA | Masi Entropy based Differential Algorithm |
| 175 | MASI-SCA | Masi Entropy based Sine–Cosine Algorithm |
| 176 | MASI-WOA | Masi Entropy based Whale Optimization Algorithm |
| 177 | MASI-GOA | Masi Entropy based Grasshopper Optimization Algorithm |
| 178 | MASI-ENG-DA | Energy Masi Entropy based Differential Algorithm |
| 179 | MASI-ENG-SCA | Energy Masi Entropy based Sine–Cosine Algorithm |
| 180 | MASI-ENG-WOA | Energy Masi Entropy based Whale Optimization Algorithm |
| 181 | MASI-ENG-GOA | Energy Masi Entropy based Grasshopper Optimization Algorithm |
| 182 | WCA | Water Cycle Algorithm |
| 183 | MBO | Monarch Butterfly Optimization |
| 184 | Masi-BA | Masi Entropy based Bat Algorithm |
| 185 | Masi-PSO | Masi Entropy based Particle Swarm Optimization |
| 186 | Masi-WDO | Masi Entropy based Wind Driven Optimization |
| 187 | Masi-MBO | Masi Entropy based Monarch Butterfly Optimization |
| 188 | Masi-GOA | Masi Entropy based Grasshopper Optimization Algorithm |
| 189 | Masi-WCA | Masi Entropy based Water Cycle Algorithm |
| 190 | Tsallis-BA | Tsallis Entropy based Bat Algorithm |
| 191 | Tsallis-PSO | Tsallis Entropy based Particle Swarm Optimization |
| 192 | Tsallis-WDO | Tsallis Entropy based Wind Driven Optimization |
| 193 | Tsallis-MBO | Tsallis Entropy based Monarch Butterfly Optimization |
| 194 | Tsallis-GOA | Tsallis Entropy based Grasshopper Optimization Algorithm |
| 195 | Tsallis-WCA | Tsallis Entropy based Water Cycle Algorithm |
| 196 | AGPSO | Autonomous Particles Groups for Particle Swarm Optimization |
| 197 | GLCM-LSSA | Gray Level Co occurrence Matrix-Salp Swarm Algorithm using Levy Flight |
| 198 | Kapur-LSSA | Kapur Entropy based Salp Swarm Algorithm using Levy Flight |
| 199 | Kapur-WOA | Kapur Entropy based Whale Optimization Algorithm |
| 200 | Kapur-FPA | Kapur Entropy based Flower Pollination Algorithm |
| SL  | Method’s name (abbreviation) | Full form                                                                 |
|-----|-----------------------------|--------------------------------------------------------------------------|
| 201 | Kapur-SOA                   | Kapur Entropy based Seeker Optimization Algorithm                        |
| 202 | Kapur-BA                    | Kapur Entropy based Bat Algorithm                                        |
| 203 | SAMFO-TH                    | Self-Adaptive Moth-Flame Optimization Thresholding Heuristic             |
| 204 | MSEPO                       | Multi-Strategy Emperor Penguin Optimizer                                  |
| 205 | IDSA                        | Improved Particle Swarm Optimization Search Algorithm                    |
| 206 | LMVO                        | Multi-Verse Optimization based on Levy Flight                              |
| 207 | EPO                         | Emperor Penguin Optimizer                                                 |
| 208 | MGOA                        | Modified Grasshopper Optimization Algorithm                               |
| 209 | MOPSO                       | Multi-Objective Particle Swarm Optimization                               |
| 210 | MOEAD                       | Multi-Objective Evolutionary Algorithm based on Decomposition             |
| 211 | MOEADR                      | Multi-Objective Differential Evolution with Ranking-based Mutation Operator |
| 212 | KnEA                        | Knee Evolutionary Algorithm                                               |
| 213 | NSGA-III                    | Non-dominated Sorting Genetic Algorithm for multi-objective optimization  |
| 214 | RVEA                        | Vector Guided Evolutionary Algorithm                                      |
| 215 | IMMOEA                      | Inverse Modeling Many-Objective Evolutionary Algorithm                    |
| 216 | LMEA                        | Large-scale Many-Objective Evolutionary Algorithm                        |
| 217 | MOEA                        | Many-Objective Evolutionary Algorithm                                    |
| 218 | BMO-DE                      | Bird Mating Optimization and Differential Evolution                        |
| 219 | MBF                         | Modified Bacterial Foraging                                              |
| 220 | PSO-DE                      | Hybrid Particle Swarm Optimization- Differential Evolution                |
| 221 | TLMOV                       | Tournament-Based Lévy Multiverse Optimization Algorithm                  |
| 222 | LMZO                        | Lévy Multiverse Optimization Algorithm                                   |
| 223 | DHHOM                       | Dynamic Harris Hawks Optimization with a Mutation Mechanism               |
| 224 | Tsallis-MGGA                | Tsallis Entropy based Modified Grasshopper Optimization Algorithm        |
| 225 | Tsallis-MABC                | Tsallis Entropy based Artificial Bee Colony                               |
| 226 | Otsu-MFPA                   | Otsu Entropy based Modified Flower Pollination Algorithm                 |
| 227 | Otsu-GWO                    | Otsu Entropy based Grey Wolf Optimization                                 |
| 228 | DPSO                        | Darwinian Particle Swarm Optimization                                    |
| 229 | FODPSO                      | Fractional Order Darwinian Particle Swarm Optimization                   |
| 230 | DA                          | Dragonfly Algorithm                                                      |
| 231 | OBLDA                       | Opposition-Based Learning- Dragonfly Algorithm                            |
| 232 | GLCM                        | Gray Level Co occurrence Matrix                                           |
| 233 | SVM                         | Support Vector Machine                                                   |
| 234 | NB                          | Naïve–Bayes                                                              |
| 235 | DT                          | Decision-Tree                                                            |
| 236 | KNN                         | K-Nearest Neighbors                                                      |
| 237 | RF                          | Random-Forest                                                            |
| 238 | FCM                         | Fuzzy C-Means                                                            |
| 239 | FLICM                       | Fuzzy Local Information C-Means                                          |
| 240 | T²NSEIF                     | Type-2 Neutrosophic-Entropy for granular feature representation          |
| 241 | MFCM                        | Modified Fuzzy C-Means                                                    |
| 242 | FKMKCA                      | Fuzzy-K-Means Clustering Algorithm                                        |
| 243 | KIFECM                      | Kernel Intuitionistic Fuzzy Entropy C-Means                              |
| 244 | NEATSA                      | Neutrosophic Entropy-Based Adaptive Thresholding Algorithm               |
| 245 | FE-TII                      | Fuzzy Entropy Type II                                                    |
| 246 | OBL                         | Opposition-Based Learning                                                |
| 247 | TSA                         | Tree Seed Algorithm                                                      |
| 248 | EM                          | Expectation Maximization                                                 |
| 249 | GLLA                        | Gray Level & Local-Average histogram                                     |
| 250 | DCM                         | Dynamic Cauchy Mutation                                                  |
and the cumulative distribution function of each class is defined as:

\[
 Ph_i = \frac{h_i}{NP}, \sum_{i=1}^{NP} Ph_i = 1, \tag{4}
\]

and the cumulative distribution function of each class is defined as:

\[
w_1 (th) = \sum_{i=1}^{th} P_h_i, \quad w_2 (th) = \sum_{i=th+1}^{L} P_h_i, \tag{5}
\]

For multi-level image segmentation, Kapur method can be extended to incorporate multi thresholding capabilities. In such case, the image is divided into \(K\) classes. Under such circumstances, Eq. (2) is redefined as:

\[
f (\mathbf{th}) = \max \left( \sum_{i=1}^{K} H_i (\mathbf{th}) \right), \tag{6}
\]

where \(\mathbf{th} = [th_1, th_2, \ldots, th_m]\), represents the vector of threshold values and the entropy values, corresponding to each threshold value for a multi-level segmentation problem is calculates as:

\[
 H_1 (th_1) = \sum_{i=1}^{th_1} \frac{P_h_i}{w_1 (th_1)} \ln \left( \frac{P_h_i}{w_1 (th_1)} \right)
\]

\[
 H_2 (th_2) = \sum_{i=th_1+1}^{th_2} \frac{P_h_i}{w_2 (th_2)} \ln \left( \frac{P_h_i}{w_2 (th_2)} \right)
\]

\[
 \ldots \quad \ldots \quad \ldots
\]

\[
 H_K (th_m) = \sum_{i=th_m+1}^{L} \frac{P_h_i}{w_K (th_m)} \ln \left( \frac{P_h_i}{w_K (th_m)} \right).
\]

The cumulative distribution function of each class is defined as:

\[
w_1 (th_1) = \sum_{i=1}^{th_1} P_h_i, \quad w_2 (th_2) = \sum_{i=th_1+1}^{th_2} P_h_i, \quad w_K (th_m) = \sum_{i=th_m+1}^{L} P_h_i. \tag{8}
\]

### 3.3 Recent literature on MLT using NIOA

This section encompasses an informed literature assessment on the usage of NIOA to solve the MLT problem. The study takes into account works that were released between 2019 and 2021. The general approach of MLT using NIOA is summarized as Algorithm 1 comprising of various steps. In the initial step i.e., Step 1, the objective function is considered. In MLT, the ideal thresholds is attained by optimizing a certain objective function or maximizing various entropy such as Kapur’s entropy, between-class variance etc. Further, the initial parameters of the population that essentially represents the solution to the given optimization problem are haphazardly initialized and created in the solution space. The fitness function, which is considered as one of the sole pointers to highlight the performance of each solution is calculated in Step 3.

The recent literature of NIOA based MLT has been presented in Table 3. Different methods and parameter’s abbreviation used in the papers surveyed in Table 3 with its full form is tabularized respectively in Tables 4 and 5. Total 88 papers have been discussed in Table 3 where 19, 31, and 38 papers are collected from the years 2021, 2020 and 2019 respectively and presented in Fig. 3a. Whereas, Fig. 3b indicates the percentage of papers which are surveyed in Table 3 utilized different types of images. The mentioned papers have been collected from the following sources:

(i) Google Scholar—http://scholar.google.com
(ii) IEEE Xplore—http://ieeexplore.ieee.org
(iii) ScienceDirect—http://www.sciencedirect.com
(iv) SpringerLink—http://www.springerlink.com
(v) DBLP—http://dblp.uni-trier.de
(vi) ACM Digital Library—http://dl.acm.org
3.4 Major challenges of NIOA based multi-level thresholding

Based on the literature, it can be practically believed that NIOA has an enormous impact over MLT problem despite of some issues pertaining to few NIOA, particularly from theoretical perspectives as summarized in Sect. 2.1 that has clearly emphasized on some realistic challenges. In addition, the challenges specifically in regard to NIOA based MLT for image segmentation. Is thereby summarized as follows:

1. Selection of NIOA for MLT: It can be noticed that a massive set of NIOA has been introduced and exist in literature. Though, theoretically and practically, each NIOA’s performance extensively depends on the problem under consideration i.e. the image type for MLT. Nonetheless, it is not at all feasible to apply each NIOA over a set of images and assess its performance. Subsequently, for a researcher, appropriate selection of NIOA for a set of images turns out to be reasonably challenging. Current tradition also illustrates the application of newly developed NIOA over MLT and highlights a rigorous comparative study with other well-established NIOA in the problem domain.

2. Selection of Objective Function: Proper selection of objective function for a NIOA based MLT model for a specific set of images is also very demanding. Numerous objective functions are developed in the literature which makes the selection more crucial for a type of images like medical or satellite. For example, Paulo claimed that Tsallis’ entropy outperformed Cross and Shannon entropies by considering the segmentation of gray level images (Rodrigues et al. 2017). Ray et. al. (2021) claimed that Tsallis entropy is better than Otsu, Cross, Fuzzy entropy, Kapur’s entropy for proper thresholding of color pathology images. Whereas, Suresh et. al. claimed that Cross entropy is superior to Tsallis’ entropy to segment satellite images (Suresh and Lal 2017). Therefore, it can be said that the efficiency of the objective functions crucially depend on the NIOA and Image type.

3. Selection of Quality Parameters: As such there is no single criterion for completing accurate segmentation for different variants of images. Furthermore, there is no one metric for evaluating the segmentation quality of an image segmentation technique across various image types (Dhal et al. 2020a). Several quality parameters have been listed in Table 4 and some of their selection will judge which NIOA based MLT model is best for the set of image type under consideration.

4. Selection of Random walk for NIOA in the MLT domain: Randomization is a crucial part of any intelligence system, including current NIOA. Randomization

Table 5 Different qualitative parameters used in the paper surveyed in Table 3 and its full form

| SL | Parameter’s abbreviation | Full form |
|----|--------------------------|-----------|
| 1  | PSNR                     | Peak Signal to Noise Ratio |
| 2  | SSIM                     | Structural Similarity Index Metric |
| 3  | FSIM                     | Feature Similarity Index Metric |
| 4  | FNR                      | False Negative Rate |
| 5  | FPR                      | False Positive Rate |
| 6  | NPV                      | Negative Predictive Value |
| 7  | ME                       | Misclassification Error |
| 8  | J-Index                  | Jaccard-Index |
| 9  | RAE                      | Relative Foreground Area Error |
| 10 | F                        | F-measure |
| 11 | IRU                      | Intra-class Region Uniform |
| 12 | JSC                      | Jaccard Similarity Coefficient |
| 13 | CC                       | Correlation Coefficient |
| 14 | UM                       | Uniformity Measure |
| 15 | NMI                      | Normalized Mutual Information |
| 16 | AMI                      | Adjusted Rand Index |
| 17 | QILV                     | Quality Index based on Local Variance |
| 18 | ME                       | Mean Squared Error |
| 19 | ERC                      | Edge Retention Coefficient |
| 20 | PRI                      | Probability Rand Index |
| 21 | Voi                      | Variation of Information |
| 22 | GCE                      | Global Consistency Error |
| 23 | BDE                      | Boundary Displacement Error |
| 24 | MSSIM                    | Mean Structural SIMilarity |
| 25 | JSC                      | Jaccard Similarity Coefficient |
| 26 | UQI                      | Universal Quality Index |
| 27 | DC                       | Dice Coefficient |
| 28 | SNR                      | Signal-to-noise ratio (SNR) |
| 29 | MAE                      | Maximum Absolute Error |
| 30 | RMSE                     | Root Mean Squared Error |
| 31 | NCC                      | Normalized Cross Correlation |
| 32 | AD                       | Average Difference |
| 33 | SC                       | Structural Content |
| 34 | NAE                      | Normalized Absolute Error |
| 35 | MAD                      | Mean Absolute Distance |
| 36 | QILV                     | Quality Index based on Local Variance |
| 37 | ME                       | Mean Error |
| 38 | IoU                      | Intersection over Union |
| 39 | GMSD                     | Gradient Magnitude Similarity Deviation |
| 40 | FDR                      | False Discovery Rate |
| 41 | PPV                      | Positive Predictive Value |
| 42 | FOR                      | False Omission Rate |
| 43 | NPV                      | Negative Predictive Value |
| 44 | MVTR                     | Mean Value to Reach |
| 45 | TVD                      | Threshold Value Distortion |
| 46 | HV                       | HyperVolume Measure |
| 47 | SP                       | Spacing Measure |
| 48 | U                        | Uniformity Measure |
allows an NIOA to leave any local optimum and search globally. Several random walks (Dhal et al. 2020b) demonstrated their effectiveness with various NIOA in various domains. Essentially, no analytical conclusions exist that proclaims which random walk is preferable for which algorithm. The application of any specific random walk, on the other hand, is entirely dependent on the problem and the NIOA in concern. As a result, choosing the right random walk during the development or improvement of NIOA is critical.

In addition to the above challenges, improvement of NIOA, their optimal parameters setting, their performance comparison in MLT based image segmentation domain are few other major challenging tasks that can be looked upon in future.

4 Experimental results

This section presents the experimental results which have been computed with the help of six NIOA and Masi entropy over satellite images. The six NIOA are Aquila Optimizer (AQO) (Abualigah et al. 2021a), Arithmetic Optimization Algorithm (AOA) (Abualigah et al. 2021b), Archimedes Optimization Algorithm (AROA) (Hashim et al. 2021), Rat Swarm Optimization Algorithm (RSA) (Dhiman et al. 2021), Particle Swarm Optimization (PSO) (Dhal et al. 2019c), and Firefly Algorithm (FA) (Dhal et al. 2020d). It can be noticed that four NIOA i.e., AQO, AOA, AROA, and RSA are developed in 2021 and they are very popular NIOA according to citation in Table 1. PSO and FA are well-established NIOA and selected to compare to these new NIOA for proving their effectiveness. Now, Masi entropy has been opted because it is state-of-the-art entropy and attracted many researchers in MLT domain over different kind of images. We maximize the Masi entropy for image segmentation. So, it is a maximization problem. For the reasonable comparison amongst NIOA methodologies, each execution of the tested objective functions considers the Number of Function Evaluations, $NFE = 1000 \times d$, as stopping criterion of the optimization process. This criterion has been designated to encourage compatibility with previously published works in the literature. The experiments are evaluated considering the number of threshold values ($TH$) set to 5, 7, and 9 which correspond to the $d$-dimensional search space in an optimization problem formulation. Furthermore, $FE$ is also a crucial performance index used to measure the efficiency of NIOA. In comparison to computational complexity, $FE$ permits some technical aspects such as the computer system where the experiments run and is implemented, that has direct impact on the running CPU time thereby concentrating only on the capacity of the algorithm to search within the solution space. For measuring the optimization ability of the NIOA, mean fitness ($\bar{f}$) and standard deviation ($\sigma$) have been calculated. On the other hand, the segmentation efficiency of the NIOA based models have been measured by computing Peak Signal-to-Noise Ratio (PSNR), Quality Index based on Local Variance (QILV), and Feature Similarity Index (FSIM). These parameters are very well-known in image segmentation domain. Table 4 highlights the list of utilized segmentation quality parameters (Dhal et al. 2020c, 2021b, 2021c; Das et al. 2021).

With the intention to verify the efficiency of different NIOA, experiment is conducted using 20 color satellite images. Further, MatlabR2018b and Windows-10 OS, x64-based PC, Intel core i5 CPU with 8 GB RAM are the hardware and software requirements incorporated during the experiment. The proposed algorithms are tried and explored on images extracted from the site of Indian Space Research Organization (ISRO) (Dhal et al. 2019b) [https://bhuvan-app1.nrsc.gov.in/imagegallery/bhuvan.html#]. Figure 4 represents the original images of different
Satellite images. The parameter setting of the NIOA is given in Table 6.

Figure 5 represents the segmented images of Fig. 4 by the tested NIOA. Table 7 signifies different parameters such as average numerical values of PSNR, QILV, FSIM, standard deviation, Computational time, and fitness function employed over satellite images to implement NIOAs with Masi entropy as an objective function. Average fitness and standard deviation clearly show that AROA provides the best results over thresholds 5, 7, and 9. PSO gives worst results among all the tested NIOAs. From Table 7, we can further conclude that if numbers of thresholds increase, value of PSNR, QILV, and FSIM also increase for the objective function. The fitness values of AROA are equated with other NIOAs using a nonparametric significance proof (Wilcoxon's rank test) (García et al. 2009). Such proof permits evaluating differences in the outcome among two related methods. Wilcoxon's rank test at the 5% significance level is used to determine if the results attained with the best performing algorithm vary statistically significantly from the final results of the other competitors. A p-value of less than 0.05 (5% significance level) sturdily supports the condemnation of the null hypothesis, thereby signifying that the best algorithm's results vary statistically noteworthy from those of the other peer algorithms and that the discrepancy is not due to chance. Table 8 reports the p-values produced by Wilcoxon's test for a pair-wise comparison of the fitness function between two groups formed as AROA vs. AOA, AROA vs. AQO, AROA vs. RSA, AROA vs. FA, and AROA vs. PSO for 5, 7, and 9 number of thresholds. All of the p-values in Table 8 are less than 0.05 (5% significance level), and h = 1 is clear proof against the null hypothesis, showing that the AROA fitness values for the performance are statistically higher, and this is not a fluke.

Table 6 Parameter setting of the NIOA

| Algorithm                | Parameters                                                                 |
|--------------------------|-----------------------------------------------------------------------------|
| Aquila Optimizer (AQO)   | For AQO, $\alpha = 0.1; \delta = 0.1$, population size (n) = 30             |
| Arithmetic Optimization Algorithm (AOA) | For AOA, $\alpha = 5; \mu = 0.5$, and population size (n) = 30               |
| Archimedes Optimization Algorithm (AROA) | For AROA, initialize $C_1, C_2, C_3$ and $C_4$ with 2, 6, 2 and 0.5 respectively and population size (n)to30 |
| Rat Swarm Optimization Algorithm (RSA) | For RSA, Control parameter (R) $\in$ (Yang 2020; Wolpert and Macready 1997), Constant Parameter $C \in [0, 2]$, population size (n)issetto30 |
| Particle Swarm Optimization (PSO) | For PSO, acceleration coefficients ($c_1, c_2$) that intends to control the outcome of local and global best solution over the current solution. For the experiment, Population size (n)isinitializedto30 |
| Firefly Algorithm (FA)   | For FA, different parameters are initialized with certain values as depicted: Attractiveness $\beta_0 = 1$, Light absorption coefficient $\gamma = 1$, Lévy flight parameters $\alpha = 0.1, \beta = 1.5$, population size (n) = 30 |
5 Conclusion and future directions

This study has three major contributions as a survey paper which are (i) A list of recent NIOA that facilitate the researchers for selecting and employing these new NIOA over different engineering optimization fields, (ii) A survey table of NIOA-based MLT for image segmentation which will give idea about the application of different NIOA with different objective functions over different kinds of images, (iii) Lastly a comparative study among some recently proposed NIOA have been performed with recently developed Masi entropy for satellite image multi-level thresholding. The experimental results are very encouraging due to the application of different NIOA over Masi entropy-based image segmentation.

Therefore, it can be easy to infer that NIOA based MLT is a fresh and exciting research topic with innovative methodologies. Applying diverse NIOA with various objective functions over several types of images is considered a complicated task. The main challenging future direction is the testing of this huge set of NIOA in MLT domain. Selection of proper objective function is also a difficult task because it is reported in literature that proper segmentation of specific kind of images is significantly dependent on objective function. Exploration of multi-objective MLT can also be a great future work. Recently

| Image | nt | AROA | AOA | AQO | RSA | FA | PSO |
|-------|----|------|-----|-----|-----|----|-----|
|       | 5  | ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | ![Image](image4.png) | ![Image](image5.png) | ![Image](image6.png) |
| **Figure 4(a)** | 7  | ![Image](image7.png) | ![Image](image8.png) | ![Image](image9.png) | ![Image](image10.png) | ![Image](image11.png) | ![Image](image12.png) |
|       | 9  | ![Image](image13.png) | ![Image](image14.png) | ![Image](image15.png) | ![Image](image16.png) | ![Image](image17.png) | ![Image](image18.png) |
|       | 5  | ![Image](image19.png) | ![Image](image20.png) | ![Image](image21.png) | ![Image](image22.png) | ![Image](image23.png) | ![Image](image24.png) |
| **Figure 4(b)** | 7  | ![Image](image25.png) | ![Image](image26.png) | ![Image](image27.png) | ![Image](image28.png) | ![Image](image29.png) | ![Image](image30.png) |
|       | 9  | ![Image](image31.png) | ![Image](image32.png) | ![Image](image33.png) | ![Image](image34.png) | ![Image](image35.png) | ![Image](image36.png) |

Fig. 5 Segmented results of NIOA using Masi entropy over 5, 7, and 9 thresholds

### 5 Conclusion and future directions

This study has three major contributions as a survey paper which are (i) A list of recent NIOA that facilitate the researchers for selecting and employing these new NIOA over different engineering optimization fields, (ii) A survey table of NIOA-based MLT for image segmentation which will give idea about the application of different NIOA with different objective functions over different kinds of images, (iii) Lastly a comparative study among some recently proposed NIOA have been performed with recently developed Masi entropy for satellite image multi-level thresholding. The experimental results are very encouraging due to the application of different NIOA over Masi entropy-based image segmentation.

Therefore, it can be easy to infer that NIOA based MLT is a fresh and exciting research topic with innovative methodologies. Applying diverse NIOA with various objective functions over several types of images is considered a complicated task. The main challenging future direction is the testing of this huge set of NIOA in MLT domain. Selection of proper objective function is also a difficult task because it is reported in literature that proper segmentation of specific kind of images is significantly dependent on objective function. Exploration of multi-objective MLT can also be a great future work. Recently
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histogram clustering has been emerged as good alternative of histogram thresholding (Dhal et al. 2021c; Das et al. 2021). Therefore, application of NIOA for histogram based image clustering can also be a good future direction. Another application of NIOA will be for fuzzy rule classifier (Zhou and Angelov 2007; Angelov and Zhou 2008) or data analytics (Angelov et al. 2017).

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### Declarations

#### Conflict of interest
On behalf of all authors, the corresponding author states that there is no conflict of interest. The authors declare that they have no conflict of interest.

#### Ethical approval
This article does not contain any studies with human participants or animals performed by any of the authors.

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#### Table 7 Numerical comparison of NIOA for Masi entropy as objective function

| Number of thresholds (nt) | NIOA | $\bar{f}$ | $\sigma_f$ | Time (s) | PSNR | QILV | FSIM |
|--------------------------|------|-----------|-----------|---------|------|------|------|
| 5                        | AROA | 35.2724   | 7.12E–10  | 4.356363| 21.57856| 0.8827| 0.9181|
|                          | AOA  | 35.2717   | 8.84E–10  | 4.440363| 21.18856| 0.8686| 0.8922|
|                          | AQO  | 35.2715   | 9.51E–09  | 5.662363| 21.17856| 0.8497| 0.8917|
|                          | RSA  | 35.2695   | 8.85E–10  | 6.436363| 21.13665| 0.8456| 0.8905|
|                          | FA   | 35.2689   | 3.48E–09  | 6.445363| 21.12856| 0.8464| 0.8906|
|                          | PSO  | 35.1555   | 9.67E–10  | 6.641363| 20.45856| 0.8382| 0.8873|
| 7                        | AROA | 41.4019   | 2.26E–10  | 5.725363| 23.14856| 0.9206| 0.9314|
|                          | AOA  | 41.3983   | 5.92E–09  | 5.602363| 23.09856| 0.9135| 0.9191|
|                          | AQO  | 41.3961   | 7.64E–10  | 6.817363| 23.07856| 0.9115| 0.9085|
|                          | RSA  | 41.3953   | 4.90E–10  | 7.045363| 22.20856| 0.9101| 0.9024|
|                          | FA   | 41.3896   | 7.17E–10  | 7.078363| 23.02856| 0.9134| 0.903 |
|                          | PSO  | 41.1121   | 9.18E–10  | 7.241363| 22.10856| 0.9048| 0.8926|
| 9                        | AROA | 46.7711   | 3.25E–10  | 5.915363| 26.13856| 0.9562| 0.9645|
|                          | AOA  | 46.7456   | 3.45E–10  | 5.825363| 25.98561| 0.9449| 0.9541|
|                          | AQO  | 46.7136   | 2.52E–10  | 7.185363| 25.95856| 0.9384| 0.9489|
|                          | RSA  | 46.7045   | 1.00E–09  | 7.405363| 24.28856| 0.9251| 0.9197|
|                          | FA   | 46.6937   | 4.60E–09  | 7.393363| 24.65856| 0.9248| 0.9244|
|                          | PSO  | 46.5771   | 4.51E–10  | 7.557363| 24.07856| 0.9129| 0.9132|

Best results are highlighted in bold

#### Table 8 Comparison among NIOA depending on Wilcoxon p-values

| Pair of NIOA | Masi entropy |
|--------------|--------------|
|              | $nt = 5$     | $nt = 7$     | $nt = 9$     |
|              | $p$ | $h$ | $p$ | $h$ | $p$ | $h$ |
| AROA vs. AOA | <0.05 | 1 | <0.05 | 1 | <0.05 | 1 |
| AROA vs. AQO | <0.05 | 1 | <0.05 | 1 | <0.05 | 1 |
| AROA vs. RSA | <0.05 | 1 | <0.05 | 1 | <0.05 | 1 |
| AROA vs. FA  | <0.05 | 1 | <0.05 | 1 | <0.05 | 1 |
| AROA vs. PSO | <0.05 | 1 | <0.05 | 1 | <0.05 | 1 |
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