Archives of Computational Methods in Engineering (2022) 29:5313–5352
https://doi.org/10.1007/s11831-022-09766-z

SURVEY ARTICLE

Human-Inspired Optimization Algorithms: Theoretical Foundations, Algorithms, Open-Research Issues and Application for Multi-Level Thresholding

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Received: 5 April 2022 / Accepted: 7 May 2022 / Published online: 7 June 2022

Abstract

Humans take immense pride in their ability to be unpredictably intelligent and despite huge advances in science over the past century; our understanding about human brain is still far from complete. In general, human being acquire the high echelon of intelligence with the ability to understand, reason, recognize, learn, innovate, retain information, make decision, communicate and further solve problem. Thereby, integrating the intelligence of human to develop the optimization technique using the human problem-solving ability would definitely take the scenario to next level thus promising an affluent solution to the real world optimization issues. However, human behavior and evolution empowers human to progress or acclimatize with their environments at rates that exceed that of other nature based evolution namely swarm, bio-inspired, plant-based or physics-chemistry based thus commencing yet additional detachment of Nature-Inspired Optimization Algorithm (NIOA) i.e. Human-Inspired Optimization Algorithms (**HIOAs**). Announcing new meta-heuristic optimization algorithms are at all times a welcome step in the research field provided it intends to address problems effectively and quickly. The family of HIOA is expanding rapidly making it difficult for the researcher to select the appropriate HIOA; moreover, in order to map the problems alongside HIOA, it requires proper understanding of the theoretical fundamental, major rules governing HIOAs as well as common structure of HIOAs. Common challenges and open research issues are yet another important concern in HIOA that needs to be addressed carefully. With this in mind, our work distinguishes HIOAs on the basis of a range of criteria and discusses the building blocks of various algorithms to achieve aforementioned objectives. Further, this paper intends to deliver an acquainted survey and analysis associated with modern compartment of NIOA engineered upon the perception of human behavior and intelligence i.e. Human-Inspired Optimization Algorithms (**HIOAs**) stressing on its theoretical foundations, applications, open research issues and their implications on color satellite image segmentation to further develop Multi-Level Thresholding (MLT) models utilizing Tsallis and t-entropy as objective functions to judge their efficacy.

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1 Introduction

Contemporary world stumble upon countless multifarious real-time predicaments in which the underlying computation quandary are incredibly intricate to resolve generally because of its unusually towering dimensionally allied search space that are non-linear, non-continuous, non-differentiable, non-convex in nature. It is not an overstatement if said that need of optimization is all over the place ranging from scheduling [1, 2] to deployment of wireless sensor networks [3, 4] to engineering design [5, 6] to robotic navigation [7] to image processing [8–10]. In more or less all these activities, one intends to accomplish certain goals by optimizing quality, profit or time as these resources are valuable and inadequately available in the real world. In such state of affairs, usage of traditional or classical optimization algorithms fall short and doubtlessly have an inadequate scope in endowing inclusive elucidations thereby becoming computationally demanding. This quest unquestionably show the ways en route for the inevitability of expansion and add-ons to the existing classical optimization techniques to evolve into progressive modern technological optimization processes dexterous enough to attain affluent way out appropriate for modern day's practical problems. Thus, Evolutionary Computation (**EC**) focuses on the study of the class of global optimization algorithm principally dealing with figurative practice of perceptions, principles, and procedures mined from the elementary understanding of how natural systems advances to support and solve composite computational problems to further arrive towards most suitable solution. Nonetheless, some prime challenges that tend to swivel around EC which demands to be addressed are: Lack of accepted benchmark problems; Lack of standard algorithms and implementations, Lack of mechanism for fine parameter control and tuning, Lack of methods to measure performance etc., Presently substantial amount of work has been carried forward concentrating typically on the procedures of natural selection thus developing new algorithms inspired by human. However, human behavior and evolution give power to human to familiarize with their atmospheres at rates that surpass that of other nature based evolution namely swarm, bio-inspired, plant-based or physics-chemistry based thus instigation yet other compartment of Nature-Inspired Optimization Algorithm (NIOA) [11–14] i.e. Human-Inspired Optimization Algorithms (HIOAs).

Due to the thought supremacy and intelligence seized by human, human do hold an exceptional position amongst the entire living creatures thus anticipating that the algorithm inspired from or based on human behavior can undoubtedly surpass other algorithms. Numerous human-inspired optimization algorithms have been proposed and the same has been applied to solve hefty set of problems as highlighted in Table 1. Given the significance of HIOAs in the variety of domains, there is a strapping requirement of a study that should provide a comprehensive overview of HIOAs highlighting and covering the entire major elements related to the algorithm. Besides, huge number of human inspired optimization algorithms is presented in the literature and every algorithm is different from another in some or the other way. Therefore, examining, reviewing and deeply learning every algorithm is not just intricate but at times not feasible so researcher who is not very familiar with HIOAs shall be constantly in a dilemma about the choice of the algorithm under variety of circumstances. This work shall try filling up the research gap thus acting as a bridge by endowing a brief yet inclusive overview of the different algorithms induced by the human experiences by analyzing, assessing, documenting and intensely testing the same over color satellite imagery. This paper classically gives attention to not just comparing of several human based meta-heuristics however, also tries to accumulate obligatory information such as fundamental building blocks, common structure opted by HIOAs, elements of HIOAs (namely nature of algorithm, number of solution, fundamental methodology followed and source of inspiration by each algorithm) and advancements in the direction of accomplishing the connotation of HIOA for MLT color satellite image segmentation and further classification of HIOA based on few criteria such as Socio-Political Philosophy, Socio-Competitive Behavior, Socio-Cultural/Socio-Interaction, Socio-Musical Ideologies and Socio-Emigration/Socio-Colonization making it easier for the new researcher to garner idea about which HIOA would be suitable for the problem they intend to resolve. A number of research challenges with HIOA are discussed. Further, open future research directions are also recommended for researchers to pursue. Total 51 well-accepted and renowned stochastic HIOAs are taken into account in the present work. Consequently, this paper provides an acquainted detail of the different HIOAs developed so far over last two decades. Further, incredibly inadequate amount of work has been carried out using HIOA in the field of image segmentation thereby this paper explores and comprehends HIOA based multilevel thresholding image segmentation carried so far and further implements and compare few popular HIOAs (six HIOAs namely Corona virus Herd Immunity Optimization **(CHIO),** Forensic-Based Investigation Optimization **(FBIO),** Battle Royale Optimization (**BRO**), Political Optimizer **(PO),** Heap-Based Optimizer (**HBO**) and Human Urbanization Algorithm (**HUA**)) for color satellite image segmentation. Further, six HIOAs are compared with a popular Swarm based optimization algorithm namely Particle Swarm Optimization (**PSO**) [15]. For the same, Tsallis entropy and newly developed t-entropy have been exploited as objective functions in this paper. The *t*-entropy has not been employed for MLT predominantly with HIOA and this paper tends to draw attention to this as a major contribution. Lastly, comparative study using the mentioned objective functions over the color satellite images in MLT domain has been carried out meticulously to investigate the effectiveness of the mentioned HIOA. Some of the Human-Inspired Optimization Algorithms (HIOA) introduced over the years has been tabulated in Table 1 along with its year of introduction, author, application areas and additionally citation has been emphasized as per Google Scholar (Dated: 21.01.2022). Further, line charts shown in Figs. 1 and 2 is employed to depict the citations of different HIOAs (Harmony Search algorithm being the highly cited) and year-wise development of HIOAs respectively. The commonly used abbreviation is tabulated in Table 2.

The remaining sections of the paper are organized as follows: The elements of HIOAs and its common structure literature are put forward in Sect. 2. Section 3 draws

Table 1 Human-Inspired Optimization Algorithms (HIOAs) and their applications

SI	Name of the HIOA	Year	Author	Application area	Citation
1	Cultural Algorithm	1994	Reynolds [35]	Power Networks [36], Wind Power Forecast [37], Distribution Network [38], Wireless Sensor Network (WSN) [3], Multi-Walled Carbon NanoTubes (MWCNTs) [39], Knowledge Integration [40, 41], Wiener and Hammerstein Nonlinear Systems Identification [42], Policies and Production Scheduling [43], Fault-Tolerance Scheduling [44], Image Classification (Image Processing) [45], Neural Network [46], Rule Mining [47], Forecasting Share Price [48]	1208
2	Harmony Search Algorithm	2001	Geem et al. [49]	Engineering Optimization Problem [50], Data Mining [51], Optimum design of steel frames [52], Robotics, Telecommunication, Health [53], Multi-thresholding [54–57]	6309
3	Society and Civilization	2003	Ray et al. [58]	Engineering design problems [58]	516
4	Seeker Optimization Algorithm	2006	Dai et al. [59]	Digital IIR filters design [60], Optimal reactive power dispatch [61], Economic dispatch problems [62], PID Controller, Hybrid Power Systems [63]	199
5	Imperialist Competitive Algorithm	2007	Gargari and Lucas [64]	Heat Exchangers [65], Linear Induction Motor [66], Data Clustering [67], Bit Error Rate Beam Forming [68], Engineering Design Problems [69], Prediction of oil flow rate [70], Mix-Outsourcing problem [71], Electromagnetic [72], PID Controller Design [73], Multi-Machine Power Systems [74], Skin Color Segmentation, Image Thresholding, Image Matching, Multi thresholding (Image Processing) [75, 76], Ground Vibration Prediction [77], Vehicle Fuzzy Controller [78], Power Flow Problem [79], Flow Shop Problem [80], Image Encryption [81]	2739
6	League Championship Algorithm	2009	Kashan [82]	Numerical Function Optimization [82], Global Optimization [83], Mechanical Engineering Design [6], Optimal Power Flow [84], Task Scheduling [85], Data Clustering [86], Extracting Stock Trading rules [87]	214
7	Group Counseling Optimization Algorithm	2010	Eita et al. [88]	Spacecraft Trajectory design problem [89], Multi-Objective Optimization problem [90]	26
8	Election Campaign Optimization Algorithm	2010	Wenge et al. [91]	PID controller parameters tuning problem [91], Pressure Vessel Design [92], Optimization problems [93]	32
9	Social Emotional Optimization Algorithm	2010	Yuechun et al. [94]	Nonlinear constrained programming problems [94], Chaotic systems [95]	62

Table 1 (continued)

SI	Name of the HIOA	Year	Author	Application area	Citation
10	Teaching Learning-Based Optimization	2011	Roa et al. [96]	Mechanical Design Problems [96], Design of Planar Steel Frames [97], Non-Linear Large Scale Problems [98], Heat Exchangers [99], Flow Shop and Job Shop Scheduling [2], Engineering Design Problems [100, 101], Design of Heat Pipe [102], Sizing Truss Structure [103], Thermoelectric Cooler [104], PID Controller [105], Foundry Industry [106], Radial Distribution System [107], Image Segmentation, Image Thresholding (Image Processing) [108]	3055
11	Brain Storm Optimization	2011	Yuhui Shi [109]	Feature Selection, Image Classification, Image Segmentation (Image Processing) [110–114], Wireless Sensor Network (WSN) [4], Robot Path Planning [7], Multi-Objective Optimization Problem [115], Clustering Analysis [116], Matching Ontologies [117], Automatic Carrier Landing System [118]	536
12	Anarchic Society Optimization	2011	Ahmadi [119]	PID controller [120], Flow Shop scheduling problem [121], Multi-Reservoir System [122], Water Distribution network [123]	51
13	Cohort Intelligence	2013	Kulkarni et al. [124]	Data Clustering [125], Optimization problems [126], Mechanical component design [127], Manufacturing process problems [128]	94
14	Cultural Evolution Algorithm	2013	Kuo et al. [129]	Engineering Problems [129]	59
15	Backtracking Search Optimization Algorithm	2013	Civicioglu [130]	Numerical Optimization problems [130], Optimal allocation of multi-type distributed generators [131], power flow [132], concentric circular antenna arrays [133], Flood forecasting [134]	886
16	Interior Search Algorithm	2014	Gandomi [135]	COVID-19 Forecasting [136], Building structure design [137], Engineering Optimization Problem [138], Feature Selection (Image Processing) [139]	337
17	Soccer League Competition Algorithm	2014	Moosavian [140]	Water Distribution Network design [140], Knapsack problems [141], Solving Non-Linear Equations [142], Wireless Sensor Network (WSN) [143], Optimization of truss structures [144]	119
18	Exchange Market Algorithm	2014	Ghorbani and Babaei [145]	Load Dispatch [146], Optimum economic and Emission dispatch [147], Color image segmentation (Image Processing) [148]	165
19	Election Algorithm	2015	Emami et al. [149]	Blockchain [150], Neural Network [151], WSN (Wireless Sensor Network) [152]	53
20	Passing Vehicle Search	2016	Savsani and Savsani [153]	Structure Optimization [154], Electro-Discharge Machining (EDM) [155], Optimal power flow problems [156], signal timing optimization [157]	133

Table 1 (continued)

SI	Name of the HIOA	Year	Author	Application area	Citation
21	Jaya Algorithm	2016	Rao [158]	Engineering Optimization Problem [159], Photovoltaic Cell [160], Surface grinding process optimization [161], Multi-thresholding [162]	1308
22	Tug of War Optimization	2016	Kaveh and Zolghadr [163]	Engineering design problems [163], Structural Damage Identification [164], Workload prediction model [165], Design of laterally-supported castellated beams [166], Water distribution system design [167]	57
23	Social Group Optimization	2016	Satapathy et al. [168]	Data Clustering [169], Optimization problems [169], Image Segmentation [170], Task Scheduling [171], Image Processing [172]	149
24	Social Learning Optimization	2016	Liu et al. [173]	QoS-aware cloud Service [173], Scheduling in Cloud Computing [174]	81
25	Football Game Algorithm	2016	Fadakar and Ebrahimi [175]	Optimization problems [175], Vehicle Routing Problem [176]	29
26	Ideology Algorithm	2016	Huan et al. [177]	Optimization problems [177]	42
27	Most Valuable Player Algorithm	2017	Bouchekara et al. [178]	PV Generation System [179], Wind farm layout optimization [180], direction over current relays coordination problem [181]	52
28	Human Behavior-Based Optimization	2017	S A Ahmadi [182]	Cell Design Problem [183], S-Box Design Problems [184], Digital Over Current Relays (DOCRs) [185]	42
29	Human Mental Search	2017	M.J. Mousavirad [186]	Image Clustering, Image Segmentation, Multi Thresholding (Image Processing) [187–190], Global Optimization Problems [191], Color Quantization [192]	79
30	Social Engineering Optimizer	2018	Amir Mohammad Fathollahi-Fard [193]	Cross Docking System [194], Intellectual Manufacturing System [195], Data Classification [196], Closed Loop Supply Chain System [197], Truss Optimization [198], Information Security [199]	135
31	Queuing Search Algorithm	2018	Jinhao Zhang et al. [200]	Engineering Design Problems [200], Feature Selection [201], Biochar System [202]	75
32	Team Game Algorithm	2018	Mahmoodabadi et al. [203]	Knapsack problem [204], Duffing-Holmes chaotic problems [205]	17
33	Socio Evolution and Learning Optimization	2018	Kumar et al. [206]	Unconstrained optimization problems [206]	93
34	Volleyball Premier League Algorithm	2018	Mogdhani et al. [207]	Multi-thresholding Image Segmentation [208], Global Optimization problem [31]	103
35	Class Topper Optimization	2018	Das et al. [209]	Data Clustering [209], Economic Load Dispatch problem [210], PID Controller design [211], WSN (Wireless Sensor Network) [212]	45
36	Focus Group	2018	Fattahi [213]	Optimization Problem [213]	13
37	Ludo Game-based Swarm Intelligence	2019	Singh et al. [214]	Global Optimization [214], Image Analysis [215]	21
38	Search and Rescue Optimization	2019	Amir Sabani et al. [216]	Engineering Design Problems [217]	41
39	Life Choice-Based Optimization	2019	Khatri et al. [218]	Engineering Design Problems [218]	11
40	Social Ski-Driver Optimization	2019	Tharwat et al. [219]	Feature Selection [220]	24

Table 1 (continued)

SI	Name of the HIOA	Year	Author	Application area	Citation
41	Gaining Sharing Knowledge-Based Algorithm	2019	Mohamed [221]	Engineering Optimization Problem [222], Image Multi-thresholding, Feature Selection (Image Processing) [223–225], Knapsack Problem [226], Solar Photovoltaic Model [227], Power System [228], Solid Transportation Problem [229]	79
42	Future Search Algorithm	2019	Elsisi [230]	Radial Distribution Network [231], Automatic Voltage Regulators [232]	18
43	Forensic-Based Investigation Optimization	2020	Shaheen [233]	Pothole Classification [234], Structural Design Problems Models [235], Global Optimization Problems [236]	0
44	Political Optimizer	2020	Qamar Askari et al. [237]	Truss Structure [238], Engineering Optimization Problem [5], Fuel Cell Parameter Estimation [239], Feature Selection (Image Processing) [240], Photovoltaic Systems [241], Antenna Arrays [242], Wind Solar-Diesel Battery Systems [243], Capacitor Allocation Problem [244], Economic Load Dispatch Problem [245]	79
45	Heap-Based Optimizer	2020	Qamar Askari et al. [246]	Industrial Solar Generation [247], Proton Exchange Membrane Fuel Cell (PEMFC) Stacks [248], Radial Feeder Distribution Systems [249], Optimal Reactive Power Dispatch [250], Optimal Power Flow Problem [251], Microgrid [252], Fog Computing [253]	64
46	Human Urbanization Algorithm	2020	H. Ghasemian et al. [254]	System Security Enhancement [255]	1
47	Battle Royale Optimization	2020	Taymaz Rahkar Farshi [256]	Artificial Neural Network (ANN) [257], Linearized Quadruple-Tank Process [258], Smart Grid System [259]	21
48	Dynastic Optimization Algorithm	2020	Wagan and Shaikh [260]	Wind Turbine Micrositing (WTM) problem [260]	16
49	Coronavirus Herd Immunity Optimization	2021	Mohammed Azmi Al-Betar [261]	Vehicle Routing Problem [262], Travelling Salesman Problem [263], Feature Selection (Image Processing) [264], Brushless DC Motor System [265], Network Reconfiguration [266], Transmission Expansion Planning [267], Microgrids [268], Intrusion Detection System [269], Vehicle Routing Problem [270]	39
50	Stock Exchange Trading Optimization	2022	Emami [271]	Numerical and Engineering Optimization problems [271]	1
51	Anti Coronavirus Optimization Algorithm	2022	Emami [272]	Multi-variable single-objective optimization problems [272]	0

attention towards the Classification of HIOAs. Additionally, challenges and open research issues have been evidently brought to light in Sect. 4. Application in MLT domain is emphasized in Sect. 5 that elaborates upon the problem formulation, objective functions utilized, literature review on HIOA in MLT domain over recent years and to end with experimental results along with the discussions on the same. Last but not the least, conclusion alongside few future research directions is offered in subsequent section i.e. Sect. 6.

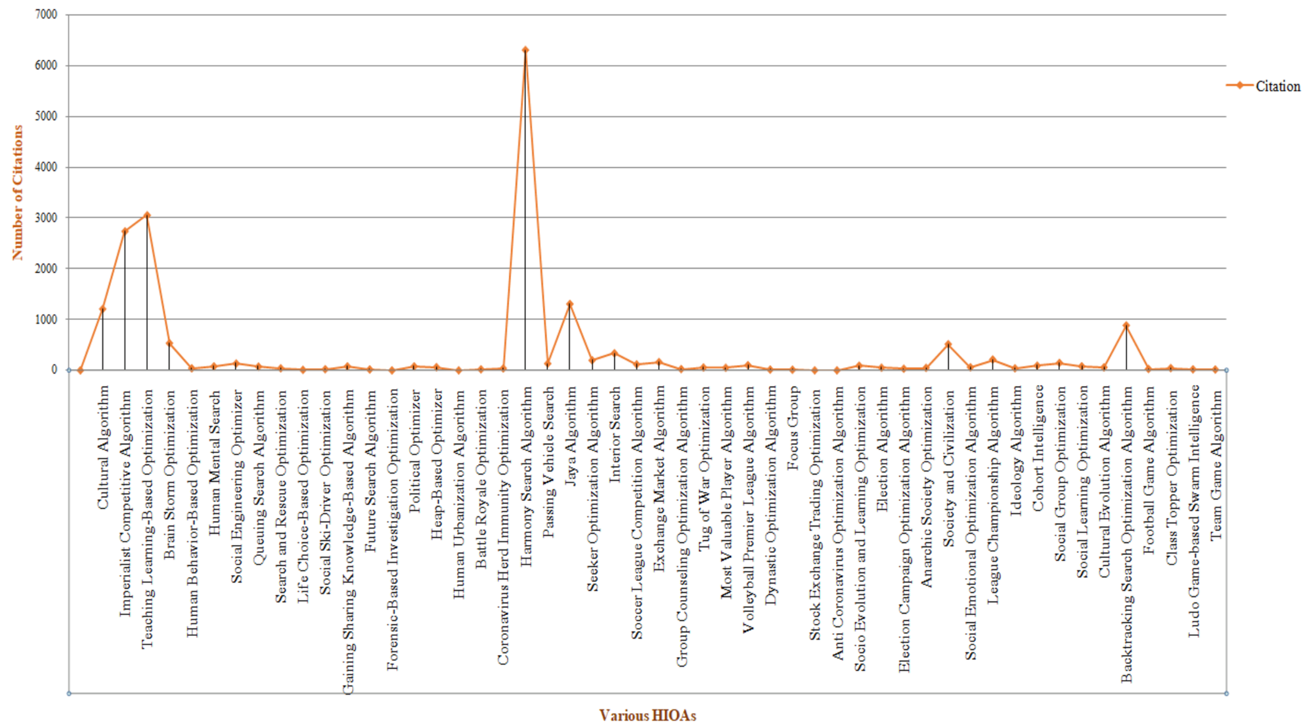

Fig. 1 The citation as per Google Scholar for various HIOAs available in literature

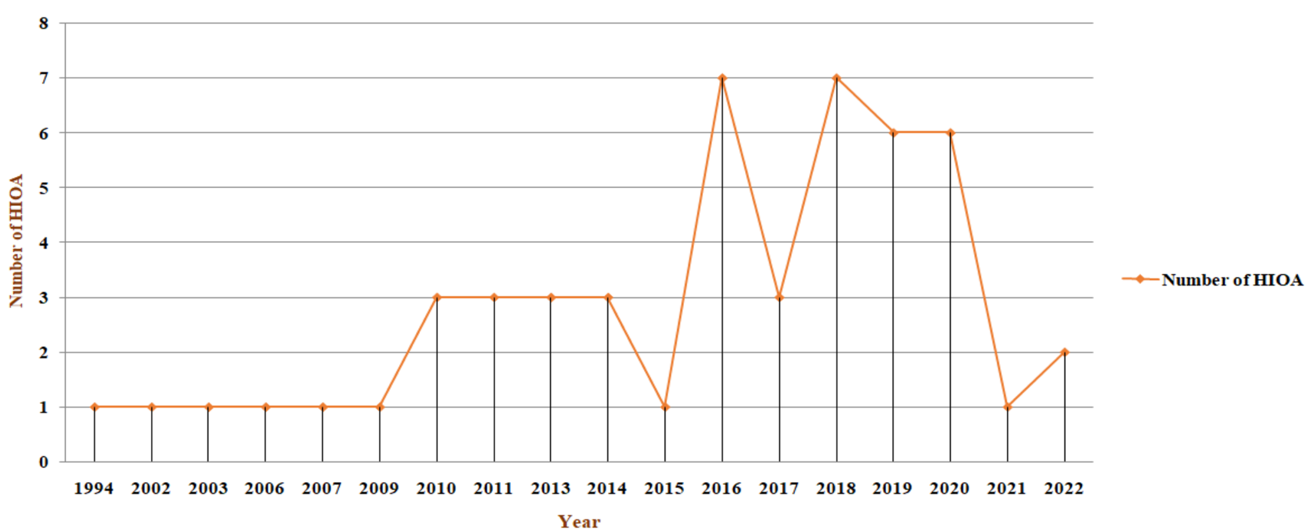

Fig. 2 Various HIOAs developed and proposed over years since 1994 till date (As per surveyed)

2 Elements of Human-Inspired Optimization Algorithms (HIOAs) and Its Common Structure

Humans have been extensively recognized as the most ingenious species across the globe acquiring abundant cognitive capabilities and processing power because of which they are referred as 'developed cultural species'. These cultural species so called human have inimitable dependence on culturally or ethnically disseminated knowledge all through the human race (across generations, across society) basically because of the socio-atmosphere around. In society (human society) every individual is speeding towards their objectives delivering the best version of own self and disseminating knowledge in one way

Table 2 Abbreviation used for Human-Inspired Optimization Algorithms (HIOAs) surveyed in this paper

Name of the HIOA	Abbreviations	Name of the HIOA	Abbreviations
Cultural Algorithm	CA	Group Counseling Optimization Algorithm	GCO
Imperialist Competitive Algorithm	ICA	Tug of War Optimization	TWO
Teaching Learning-Based Optimization	TLBO	Most Valuable Player Algorithm	MVP
Brain Storm Optimization	BSO	Volleyball Premier League Algorithm	VPL
Human Behavior-Based Optimization	HBBO	Dynastic Optimization Algorithm	DOA
Human Mental Search	HMS	Focus Group	FG
Social Engineering Optimizer	SEO	Stock Exchange Trading Optimization	SETO
Queuing Search Algorithm	QS	Anti Corona virus Optimization Algorithm	ACVO
Search and Rescue Optimization	SRO	Socio Evolution and Learning Optimization	SELO
Life Choice-Based Optimization	LCBO	Election Algorithm	EA
Social Ski-Driver Optimization	SSD	Election Campaign Optimization Algorithm	ECO
Gaining Sharing Knowledge-Based Algorithm	GSK	Anarchic Society Optimization	ASO
Future Search Algorithm	FSA	Society and Civilization	SC
Forensic-Based Investigation Optimization	FBIO	Social Emotional Optimization Algorithm	SEOA
Political Optimizer	PO	League Championship Algorithm	LCA
Heap-Based Optimizer	HBO	Ideology Algorithm	IA
Human Urbanization Algorithm	HUA	Cohort Intelligence	CI
Battle Royale Optimization	BRO	Social Group Optimization	SGO
Corona virus Herd Immunity Optimization	CHIO	Social Learning Optimization	SLO
Harmony Search Algorithm	HSA	Cultural Evolution Algorithm	CEA
Passing Vehicle Search	PVS	Backtracking Search Optimization Algorithm	BSA
Jaya Algorithm	JAYA	Football Game Algorithm	FGA
Seeker Optimization Algorithm	SOA	Class Topper Optimization	CTO
Interior Search Algorithm	ISA	Ludo Game-based Swarm Intelligence	LGSI
Soccer League Competition Algorithm	SLC	Team Game Algorithm	TGA
Exchange Market Algorithm	EMA		

or the other may it be in the field of sports, politics, music, stock market or searching a suitable place for oneself. Thereby such rapid movement of human to attain their goals leads to one important concept known as competition in the society. Considering all these, the plentiful available variants of Human inspired Optimization Algorithms, are solely inspired by the different factors associated with human and the supporting environment. This section basically draws attention towards the same i.e. the different resource of inspiration as one of the component. Apart from that, Table 3 summarizes the list of HIOAs emphasizing on the methodologies opt by each, nature of each of the HIOAs, source of inspiration for each HIOAs and number of solutions that each HIOAs generate. Beside, this section also highlights the fact that though different HIOAs tag along expansive set of perceptions however, fundamental methodologies remain the same for all. Despite the fact that HIOA has progressed significantly over the years, it is being widely applied in several research domain and application areas are thereby growing with each passing years. This calls for the necessity of a universal framework / structure making it simpler for the researcher in terms of realization. With this perception in mind, and scrounging the aid from Table 3, a common framework for HIOAs has been planned and the same is projected via a flowchart in Fig. 3. The majority of HIOA tag along the common structure that basically consist of five imperative steps namely Initialization process, Evaluation process, Construction process, Update process and Decision process.

3 Classification of Human-Inspired Optimization Algorithms (HIOAs)

There are 51 Human Inspired Optimization Algorithms have been surveyed as listed in Table 3. In this section, a variety of categorization criterion is taken into account to classify HIOAs and the same has been recorded in Table 4 and diagrammatically depicted in Fig. 4. Further out of the total HIOAs surveyed, number of HIOAs falling under the designated category has been highlighted in Fig. 5. Classifying any algorithms based on source of inspiration is quite common yet effectual. Thereby, in this paper as well

Table 3 Summary of the different components related to Human-Inspired Optimization Algorithms (HIOA)

SI	Name of the HIOA	Number of solution (single/multiple)	Nature of algorithm (stochastic/deterministic)	Source of inspiration	Methodology opted
1	Cultural Algorithm	Multiple	Stochastic	Cultural evolution as a process of dual inheritance	Initialization of population and Belief Space, Fitness Evaluation, Updating of Belief Space, Influence the population space, Termination
2	Imperialist Competitive Algorithm	Multiple	Stochastic	Imperialistic competition (Empire, Power, Colonies)	Generating Initial Empires, Moving colonies towards Imperialist, Exchanging Position, Total power of empire calculation, Imperialistic Competition, Eliminating the powerless empires, Convergence
3	Teaching Learning-Based Optimization	Multiple	Stochastic	Interaction amongst teacher and learner	Initialization, Education, Consultation, Field Changing Probability, Finalization
4	Brain Storm Optimization	Multiple	Stochastic	Human brainstorming process	Initialization, Clustering, Evaluating and Ranking individual, Generate new individual, Termination
5	Human Behavior-Based Optimization	Multiple	Stochastic	Human Behavior (Education, path selection towards success)	Initialization, Education, Consultation, Field changing probability, Finalization
6	Human Mental Search	Multiple	Stochastic	Exploration strategies of the bid space in online auctions	Initialization, Mental Search, Grouping, Moving, Termination
7	Social Engineering Optimizer	Multiple	Stochastic	Social Engineering (Attacker and Defender)	Initialize attacker and defender, Train and retrain, Spot an attack, Respond to attack, Spot a new defender, Stopping Condition
8	Queuing Search Algorithm	Multiple	Stochastic	Human activities in queuing	Initialize population, Evaluate fitness, Update individual procedure in business phase 1, phase 2 and phase 3, Termination
9	Search and Rescue Optimization	Multiple	Stochastic	Explorations behavior during search and rescue operations	Initialization, Social phase, Individual phase, Boundary Control, Updating information and position, Abandoning clues, Control parameters, Termination
10	Life Choice-Based Optimization	Multiple	Stochastic	Decision making ability of human	Initialization, Learning from the common best group, Knowing, Reviewing mistakes, Termination
11	Social Ski-Driver Optimization	Multiple	Stochastic	Paths that ski-drivers take downhill	Initialization, Position of the agents, Local and global best position, Velocity of agents, Finalization
12	Gaining Sharing Knowledge-Based Algorithm	Multiple	Stochastic	Gaining and sharing knowledge during the human life span	Initialization, Gained and Shared dimensions of both junior and senior phases, Local and global update, Finalization
13	Future Search Algorithm	Multiple	Stochastic	Human behavior to find the best life around the world	Initialization, Local search between people, Global search between the histories optimal persons, Update, Termination

Table 3 (continued)

SI	Name of the HIOA	Number of solution (single/multiple)	Nature of algorithm (stochastic/deterministic)	Source of inspiration	Methodology opted
14	Forensic-Based Investigation Optimization	Multiple	Stochastic	Suspect investigation-location-pursuit process that is used by police officers	Initialization, Cyclic investigation process, Investigation team process, Pursuit team process, Termination
15	Political Optimizer	Multiple	Stochastic	Multi-phased process of politics	Initialization (Party members), Fitness calculation, Party leaders and constituency winner identification and formation, Election Campaign, Party Switching, Parliamentary affairs (Exploitation and Convergence), Finalization
16	Heap-Based Optimizer	Multiple	Stochastic	Heap data structure to map the concept of CRH (Corporate Rank Hierarchy)	Initialization, Building Heap (Modeling CRH, interaction between the subordinates and the immediate boss, interaction between the colleagues, Employee contribution), Finalization
17	Human Urbanization Algorithm	Multiple	Stochastic	Human Behavior (adventure of finding new places, migration for better life)	Initialization (to amend city centers), Update city centers, population, Searching process, Update capital, Finalization
18	Battle Royale Optimization	Multiple	Stochastic	Genre of digital games known as ''Battle Royale'' (Search for safest place for survival)	Initialization, Compare nearest soldier (damaged, victorious), Shrink problem space, Selection, Termination
19	Coronavirus Herd Immunity Optimization	Multiple	Stochastic	Herd immunity concept as a way to tackle coronavirus pandemic (COVID-19)	Initialization, Inspiration, Generate and Evolve Herd Immunity, Population Hierarchy, Update Immunity population, Fatality cases, Termination
20	Harmony Search Algorithm	Multiple	Stochastic	Composing a piece of music	Initialization (HM: Harmony Memory), Improvise new Harmony from HM, Comparing new Harmony, Termination
21	Passing Vehicle Search	Multiple	Stochastic	Experience of driving a vehicle on two lane highway	Initialization (back vehicle (BV), front vehicle (FV), and oncoming vehicle (OV)), Distance and velocity calculation (BV and FV, FV and OV), Primary and Secondary condition checking, Finalization
22	Jaya Algorithm	Multiple	Stochastic	Striving to become victorious (towards success)	Initialization, Best and worst solution identification, Solution modification, Accept / Replace, termination
23	Seeker Optimization Algorithm	Multiple	Stochastic	Act of humans' intelligent search with their memory, experience, and uncertainty reasoning	Initialization, Position generation, Seeker evaluation, Position updation (Start point vector, Search direction, Search Radius, Trust degree), Termination

Table 3 (continued)

SI	Name of the HIOA	Number of solution (single/multiple)	Nature of algorithm (stochastic/deterministic)	Source of inspiration	Methodology opted
24	Interior Search Algorithm	Multiple	Stochastic	Interior design procedure (analysis and integration of knowledge into the creative process)	Initialization, Location generation, Fittest element identification, Element division (Composite and Mirror group), Local and global best update, Termination
25	Soccer League Competition Algorithm	Multiple	Stochastic	Soccer leagues (competitions among teams and players)	Initialization, Sample generation, League start, Team assessment, League Updation, Relegation and Promotion, Competition termination
26	Exchange Market Algorithm	Multiple	Stochastic	Procedure of trading the shares on stock market	Initialization, Stock attribution, Shareholders costs and ranking calculation, Applying changes (balance market and oscillation market condition), Termination
27	Group Counseling Optimization Algorithm	Multiple	Stochastic	Group counseling behavior of humans in solving their problems	Initialization, Solution vector substitution, Component wise production (Self counseling or member counseling), Fitness value evaluation, finalization
28	Tug of War Optimization	Multiple	Stochastic	Concept of the game “tug of war”	Initialization, Candidate design evaluation, Weight assignment, Competition and Displacement, League updation, Side constraint handling, Termination
29	Most Valuable Player Algorithm	Multiple	Stochastic	Sport where players form teams, compete collectively in order to win the championship and MVP trophy	Initialization, Team formation, Competition phase (Individual, Team). Application of greediness and elitism, Duplicate removal, termination
30	Volleyball Premier League Algorithm	Multiple	Stochastic	Competition and interaction among volleyball teams during a season	Initialization, Match Schedule, Competition, Knowledge sharing strategy, Strategy repositioning, Substitution strategy, Winner strategy, Learning phase, Promotion and Relegation process, Termination
31	Dynastic Optimization Algorithm	Multiple	Stochastic	Social behavior in human dynasties	Initialization, Random population generation (Ruler, Worker, Explorer ranking), Localized stochastic search, Best ruler selection, Termination
32	Focus Group	Multiple	Stochastic	Behavior of group members(Idea sharing, improving solutions (cooperation and discussion))	Initialization, Solution submission, Values allocation to solution, Best solution identified, Early convergence prevention, Finalization

Table 3 (continued)

SI	Name of the HIOA	Number of solution (single/multiple)	Nature of algorithm (stochastic/deterministic)	Source of inspiration	Methodology opted
33	Stock Exchange Trading Optimization	Multiple	Stochastic	Behavior of traders and stock price changes in the stock market	Initialization, Defining fitness function, Population share generation, Finding fitness share, Compute growth (rising phase), correction of share (falling phase), Replace share (Exchange phase), Relative Strength Index (RSI) calculation, Termination
34	Anti Coronavirus Optimization Algorithm	Multiple	Stochastic	Measures taken by human (Social Distancing, Quarantine, Isolation)	Initialization, Defining fitness function, Social Distancing, Quarantine (Suspect), Isolate (Infected), Fittest person generation, Finalization
35	Socio Evolution and Learning Optimization	Multiple	Stochastic	Social learning behavior of humans organized as families in a societal setup	Initialization, Parent Follow Behavior / Parent Influence function, Kid Follow Behavior / Kid Influence function, Sampling Interval Updation, Exploitation, Convergence and further research, Termination
36	Election Algorithm	Multiple	Stochastic	Presidential election	Initialization, Variable representation and eligibility function selection, Initial party creation, Positive advertisement, Negative advertisement, Coalition, Condition revision, Termination
37	Election Campaign Optimization Algorithm	Multiple	Stochastic	Election Campaign (Socio-political processes of human ideologies)	Initialization, Candidate prestige and effect range calculation, Local and global survey sample voters generation, Support of voters computed, Support bary center of the candidates computed, Finalization
38	Anarchic Society Optimization	Multiple	Stochastic	Social grouping (members behave anarchically to improve their situations)	Initialization, Movement planning(based on current, other and past positions), Index calculation, Selection of movement policy, Position updation, Termination
39	Society and Civilization	Multiple	Stochastic	Intra and intersociety interactions within a formal society	Initialization, Individual evaluation, Society building, Leader identification (Society and Civilization), Leader movement (new location), Termination
40	Social Emotional Optimization Algorithm	Multiple	Stochastic	People trying to find best path to earn higher rewards from society (Society status)	Initialization, Behavior selection (Emotional Index), Society feedback generation, Emotion index updation, Termination
41	League Championship Algorithm	Multiple	Stochastic	Competition of sport teams in a sport league	Initialization, League schedule generation, Initialize team formation, Winner / Loser determination, New formation, Identifying the fittest formation, Termination

Table 3 (continued)

SI	Name of the HIOA	Number of solution (single/multiple)	Nature of algorithm (stochastic/deterministic)	Source of inspiration	Methodology opted
42	Ideology Algorithm	Multiple	Stochastic	Self-interested and competitive behavior of political party individuals	Initialization, Party formation, Evaluation, Local Party Ranking, Competition and Improvement for local party leader, Updating party individuals, Convergence, Termination
43	Cohort Intelligence	Multiple	Stochastic	Natural and social tendency of learning from one another	Initialization, Probability (Behavior of candidate in cohort) calculation, Behavior selection, Shrink / Expand Sampling interval, Updation, Termination
44	Social Group Optimization	Multiple	Stochastic	Social behavior of human toward solving a complex problem	Initialization, Fitness calculation, Global best solution identification, Improving phase, Acquiring phase, Termination
45	Social Learning Optimization	Multiple	Stochastic	Evolution process of human intelligence and the social learning theory	Initialization, Initial Genetic Evolution phase, Individual Learning phase, Culture Influence phase, Best solution identified, Termination
46	Cultural Evolution Algorithm	Multiple	Stochastic	Socio-cultural transition (diverse cultural population evolution based on communication, infection, and learning)	Initialization, Initial Culture creation, cultural population evolution (Reserve elitist cultural species, Cultural species evolution), Cultural population merging, Termination
47	Backtracking Search Optimization Algorithm	Multiple	Stochastic	Intelligent search with experience	Initialization, Selection 1(Determination of historical population), Mutation, Crossover, Selection 2 (Fitness value), Export global minimum, Termination
48	Football Game Algorithm	Multiple	Stochastic	Players' behavior during a game for finding best positions to score a goal under supervision (coach)	Initialization, Individual fitness evaluation, Player movement, Coaching (Attacking, Substitution), Local solution, Position updation, Termination
49	Class Topper Optimization	Multiple	Stochastic	Learning intelligence of students in a class	Initialization, Examination, Learning (Section level and Student level), Performance evaluation, Performance Index calculation, Topper Selection, Termination
50	Ludo Game-based Swarm Intelligence	Multiple	Stochastic	Rules of playing the Ludo using two or four players	Initialization, fitness calculation, Best token identification, Position updation, Termination
51	Team Game Algorithm	Multiple	Stochastic	Team games (Interaction, cooperation)	Initialization, Application of operators(Passing, Mistake and Substitution operators), Identification of out of field player, Termination

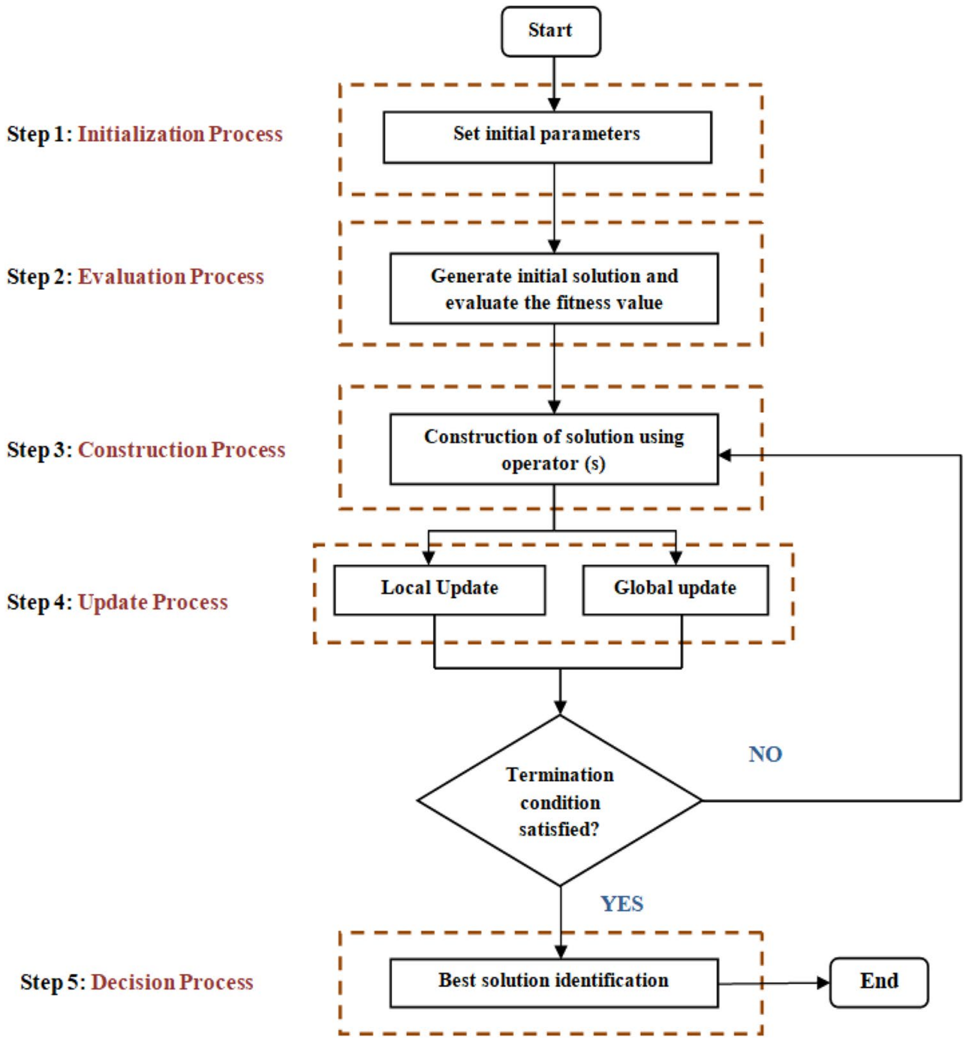

Fig. 3 Flowchart depicting common structure of HIOAs

the categorization is carried out with in the similar way i.e. using source of inspiration(a scrupulous realm HIOA emulates) and based on the same, categories such as Socio-Political Philosophy **(Political HIOA)**, Socio-Competitive Behavior **(Competitive HIOA)**, **Socio-Cultural / Socio-**Interaction **(Interactive HIOA)**, Socio-Musical Ideologies **(Musical HIOA)** and Socio-Emigration / Socio-Colonization **(Emigrational HIOA)** has been formulated.

4 Major Challenges and Open Research Issues

Although HIOAs have proved its efficacy and recognition in numerous application domains, nevertheless quite a few challenging issues predominantly from theoretical viewpoint related to such algorithms does prevail [16]. The basic methodology of all HIOAs is even though revealed evidently for the researcher however, under what exact circumstance these algorithms needs to be employed remain a foremost challenge. Further, the entire HIOAs comprises of parameters that are essentially reliant on algorithm. The lack of general mechanism to finely tune the parameter scrupulously to enhance the performance of the underlying algorithm is yet an added challenge for the researcher to look upon. Additionally, various HIOAs need to be compared and the conclusion is driven totally based on the performance parameters employed to do the same. With this comes a new challenge that researcher requires to glance ahead i.e. the choice of suitable performance parameters. Furthermore, it is quite evident that HIOAs is associated with diverse applications [Table 3 clearly highlights the same] involving diminutive or restrained problem size, nonetheless, if these algorithm can be scaled up by means of approaches like of parallel computing is still a core inquest yet to be responded.

Few open research issues have been highlighted below:

(a) Constructing a **unified mathematical framework for HIOAs**. To facilitate such integrated structure, multi-

Table 4 Classification of Human-Inspired Optimization Algorithms (HIOA) as per source of inspiration

SI	Name of the HIOA	Classification of HIOA				
		Socio-Political Philosophy	Socio-Competitive Behavior	Socio-Cultural / Socio-Interaction	Socio-Musical Ideologies	Socio-Emigration / Socio-Colonization
		Political HIOA	Competitive HIOA	Interactive HIOA	Musical HIOA	Emigrational HIOA
1	Cultural Algorithm	×	×	✓	×	×
2	Imperialist Competitive Algorithm	×	×	×	×	✓
3	Teaching Learning-Based Optimization	×	×	✓	×	×
4	Brain Storm Optimization	×	×	✓	×	×
5	Human Behavior-Based Optimization	×	×	✓	×	×
6	Human Mental Search	×	×	✓	×	×
7	Social Engineering Optimizer	×	×	✓	×	×
8	Queuing Search Algorithm	×	×	✓	×	×
9	Search and Rescue Optimization	×	×	✓	×	×
10	Life Choice-Based Optimization	×	×	✓	×	×
11	Social Ski-Driver Optimization	×	×	✓	×	×
12	Gaining Sharing Knowledge-Based Algorithm	×	×	✓	×	×
13	Future Search Algorithm	×	×	✓	×	×
14	Forensic-Based Investigation Optimization	×	×	✓	×	×
15	Political Optimizer	✓	×	×	×	×
16	Heap-Based Optimizer	×	×		×	×
17	Human Urbanization Algorithm	×	×	×	×	
18	Battle Royale Optimization	×	✓	×	×	×
19	Coronavirus Herd Immunity Optimization	×	×	✓	×	×
20	Harmony Search Algorithm	×	×	×	✓	×
21	Passing Vehicle Search	×	×	✓	×	×
22	Jaya Algorithm	×	×	✓	×	×
23	Seeker Optimization Algorithm	×	×	✓	×	×
24	Interior Search	×	×	✓	×	×
25	Soccer League Competition Algorithm	×	✓	×	×	×
26	Exchange Market Algorithm	×	×	✓	×	×
27	Group Counseling Optimization Algorithm	×	×	✓	×	×
28	Tug of War Optimization	×	✓	×	×	×
29	Most Valuable Player Algorithm	×	✓	×	×	×
30	Volleyball Premier League Algorithm	×	✓	×	×	×
31	Dynastic Optimization Algorithm	✓	×	×	×	×

Table 4 (continued)

SI	Name of the HIOA	Classification of HIOA				
		Socio-Political Philosophy	Socio-Competitive Behavior	Socio-Cultural / Socio-Interaction	Socio-Musical Ideologies	Socio-Emigration / Socio-Colonization
		Political HIOA	Competitive HIOA	Interactive HIOA	Musical HIOA	Emigrational HIOA
32	Focus Group	×	×		×	×
33	Stock Exchange Trading Optimization	×	×		×	×
34	Anti Coronavirus Optimization Algorithm	×	×	✓	×	×
35	Socio Evolution and Learning Optimization	×	×	✓	×	×
36	Election Algorithm	✓	×	×	×	×
37	Election Campaign Optimization Algorithm	✓	×	×	×	×
38	Anarchic Society Optimization	✓	×	×	×	×
39	Society and Civilization	×	×	✓	×	×
40	Social Emotional Optimization Algorithm	×	×	✓	×	×
41	League Championship Algorithm	×	✓	×	×	×
42	Ideology Algorithm	✓	×	×	×	×
43	Cohort Intelligence	×	×	✓	×	×
44	Social Group Optimization	×	×	✓	×	×
45	Social Learning Optimization	×	×	✓	×	×
46	Cultural Evolution Algorithm	×	×	✓	×	×
47	Backtracking Search Optimization Algorithm	×	×	✓	×	×
48	Football Game Algorithm	×	✓	×	×	×
49	Class Topper Optimization	×	✓	×	×	×
50	Ludo Game-based Swarm Intelligence	×	✓	×	×	×
51	Team Game Algorithm	×	✓	×	×	×

disciplinary approach to learn algorithm from diverse viewpoint is the requirement.

(b) **Self-tuning framework for HIOAs** is another challenging research issue. To achieve the same, bi-objective process for parameter tuning needs to be considered wherein algorithm to be tuned can be used to tune itself.

(c) Significance of benchmarks and **identifying useful benchmarking** to test different HIOAs.

(d) **Deciding on appropriate performance measures** for fairly comparing different HOAs. To achieve the same, unified framework for comparison of algorithm is the necessity.

(e) Introduction of **mechanism to scale up HIOAs** to handle broad range of predicaments. In order to achieve the same, generalized method need to be established that would cater to the need of variants of problems ranging from small-scale to large scale to real life problems.

(f) Establishing ways and measures to accomplish most **favorable balance of Intensification and Diversification** in HIOAs.

(g) Launching of techniques to successfully **cope up with nonlinear restraints**.

(h) Coming up with **approaches to utilize HIOAs in the realm of Machine Learning and Deep Learning**.

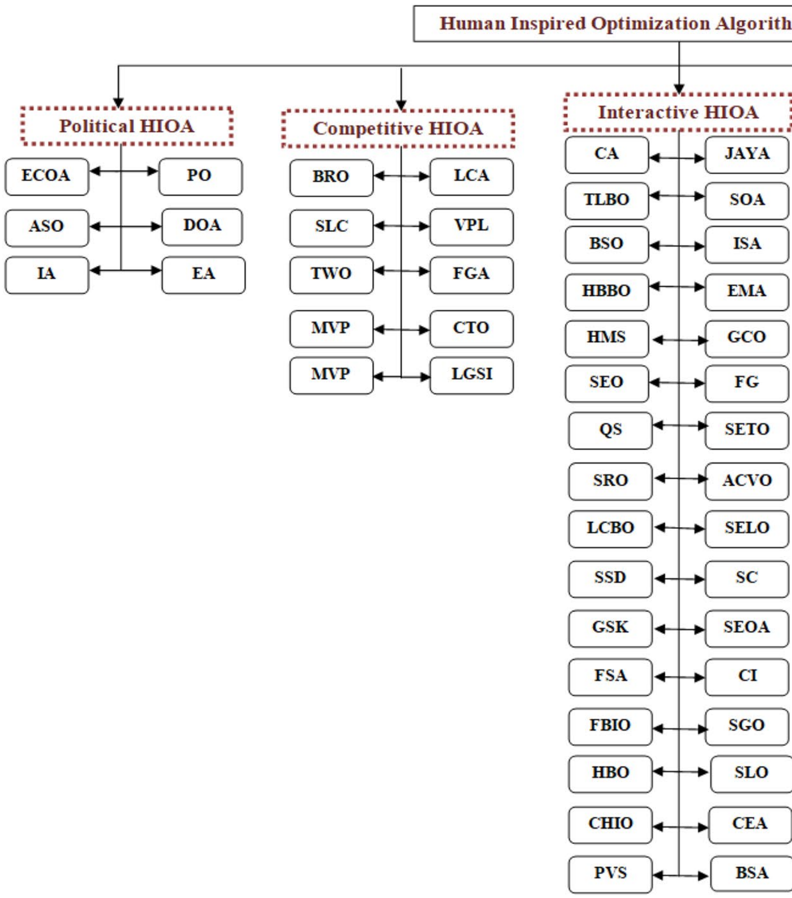

Fig. 4 Classification hierarchy of Human-Inspired Optimization Algorithms (HIOA) as per Table 4

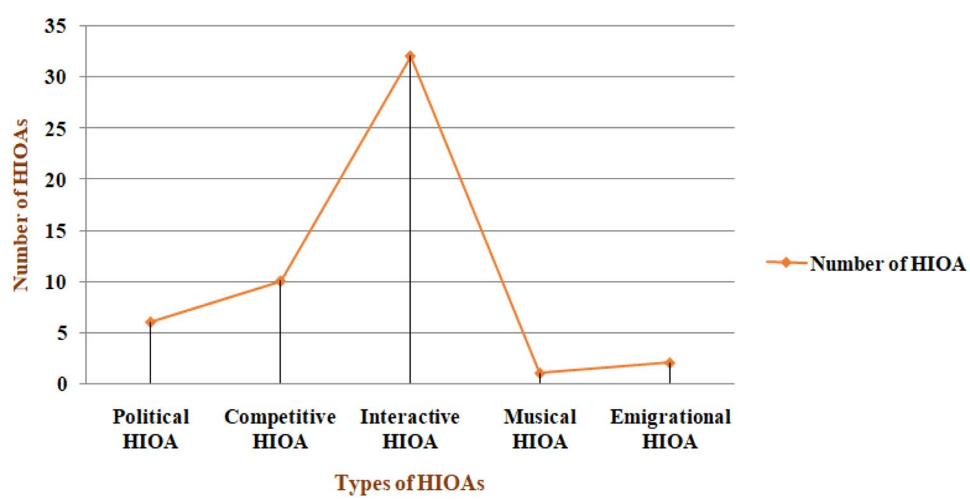

Fig. 5 Number of Human-Inspired Optimization Algorithms (HIOA) under different categories

5 Application of HIOAs in Multi-Level Thresholding Domain

Image segmentation [17, 18] is essentially the foremost and elementary procedure to examine and construe the acquired image in innumerable computer vision applications [19] wherein thresholding is considered enormously imperative in this domain. Considering the two categories of thresholding namely bi-level and multilevel, Multilevel Thresholding (**MLT**) segmentation methods has certain limitation while making a search for the best thresholding values comprehensively to optimize the objective function in which thresholding values increases thus swelling the computational cost. In simpler words, MLT methods turn out to be computationally complex as the number of thresholds grows. In order to address such imperfection and resolve other issues related to MLT, researchers are captivated towards quite a few methodologies inspired either by nature or from human behavior that can be extensively employed.

5.1 Problem Formulation

The fundamental notion of multi-level thresholding is to discover more than one threshold for a given image that further permits the images that has been segmented to accomplish the required criterion by optimizing specific objective function/s, with the threshold values as input parameters [20]. Assume that the image f comprising of L gray levels needs to be segmented into p partitions $\left(C_1, C_2, \ldots, C_i, \ldots C_p\right)$ using set of (p-1) threshold values $TH = \left(t_1, t_2, \ldots, t_i, ..., t_{p-1}\right)$, 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 [20]. 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:

$$TH^{opt} = \underset{0 \le TH \le L-1}{\arg\max / \min} \{F(TH)\} \tag{1}$$

For multi objective MLT, $F(TH) = \left(F_1(TH), F_2(TH), \ldots, F_j(TH), \ldots, F_n(TH)\right)$, where n > 1.

5.2 Objective Functions

Selection of objective functions plays a crucial role in Multi-Level Thresholding-based image segmentation. Though numerous objective functions are proposed and available widely in the literature however, that makes it even more difficult in terms of selection when an image type varies making objective functions critically dependent on the algorithm as well as image type. This section elaborates on the two objective functions namely Tsallis and t-entropy that have been considered alongside six HIOAs in MLT domain for the color satellite image segmentation.

5.2.1 Tsallis Entropy

Multi-level thresholding [21] seeks to find the best threshold values for segmenting an image into different groups while maintaining a desired property (objective function). The threshold values are used as decision variables in the optimization process, which includes maximization or minimization of an objective function.

Suppose, an image I with L gray levels are classified into K classes $\left(C_1, C_2, \ldots, C_i, \ldots C_K\right)$ using a set of nt threshold point $T = \left(th_1, th_2, \ldots, th_i, ..., th_{K-1}\right)$, where $th_1 < th_2 <, \ldots ., < th_{K-1}$. Here for 8 bit image L = 256 and gray level lie within the range [0, 255]. Therefore, a pixel with gray level g is belongs to class C_i if $t_{i-1} < g < t_i$ for $i = 1, 2, \ldots, K$. Thus single objective thresholding problem is the process of selecting the set of thresholds T′ which optimizes the objective function F(T) such that

$$T' = \arg\max / \min_{0 \le T \le L-1} \{F(T)\} \tag{2}$$

where, the objective function F(T) represents the desired property to be satisfied in order to obtain the segmented image I. In this paper, Tsallis entropy has been taken as objective function and the brief mathematical implementation of that is presented as follows.

Tsallis entropy is the generalization of Boltzmann–Gibbs entropy measure which is introduced by Constant in Tsallis [14, 22]. Based on the concept of multi-fractal theory, Tsallis entropy measure can be generalized to a non-extensive system using an entropy formula given in Eq. (3).

$$S_q = \frac{1 - \sum_{i=1}^{k} \left(p_i\right)^q}{q - 1} \tag{3}$$

where, $0 \le p_i \le 1$ denotes the probability of the state i. In the case of gray level image, it represents the occurrence of the ith gray level in the image. Tsallis parameter q signifies the measure of non-extensivity of the system under consideration. By applying pseudo additivity entropy rule it can be written as:

$$S_q(f+b) = S_q(f) + S_q(b) + (1-q).S_q(f).S_q(b) \tag{4}$$

Here, f and b represent the foreground and background classes of the image which is separated by threshold value t. Suppose,

$$\left\{ \begin{array}{l} (\mathrm{p_1}, \mathrm{p_2}, \dots\dots\dots, \mathrm{p_L}) | \mathrm{p_i} \geq 0, \mathrm{i} = 1, 2, \dots..., \mathrm{L}.; \\ \mathrm{L} = \text{number of discrete gray levels}; \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{p_i} = 1 \end{array} \right\}$$ is the probability distribution of the gray level intensities of the image. Then the probability distribution of the f and b classes are given by the following expression:

$$P_f = \frac{p_1}{P^f}, \frac{p_2}{P^f}, \dots, \frac{p_t}{P^f} \text{ and } P_b = \frac{p_{t+1}}{P^b}, \frac{p_{t+2}}{P^b}, \dots, \frac{p_L}{P^b} \tag{5}$$

where,

$$P^f = \sum_{i=1}^{t_1} p_i \text{ and } P^b = \sum_{i=t+1}^{L} p_i \tag{6}$$

Consequently for each class, Tsallis entropy can be formulated as:

$$S_q^f(t) = \frac{1 - \sum_{i=1}^{t} \left(p_i/P^f\right)^q}{q-1}, \quad S_q^b(t) = \frac{1 - \sum_{i=t+1}^{L} \left(p_i/P^b\right)^q}{q-1} \tag{7}$$

For bi-thresholding, sum of the both information measure for foreground and background is maximized. Therefore, the finding of optimal threshold can be formulated as follows:

$$t_{opt} = \text{Arg max}\left[S_q^f(t) + S_q^b(t) + (1-q)\cdot S_q^f(t)\cdot S_q^b(t)\right] \tag{8}$$

Subject to the following constraints:
$\left|P^f + P^b\right| - 1 < S < 1 - \left|P^f + P^b\right|$ where,
$S(t) = S = S_q^f(t) + S_q^b(t) + (1-q)\cdot S_q^f(t)\cdot S_q^b(t)(45)$.

This formulation can be easily extended to multi-level by the following expression:

$$\left(t_1, t_2, \dots\dots, t_m\right) = \text{Arg max}\left[S_q^1(t) + S_q^2(t) + \dots + S_q^M(t) + (1-q)\cdot S_q^1(t)\cdot S_q^2(t)\dots..S_q^M(t)\right] \tag{9}$$

where,

$$S_q^1(t) = \frac{1 - \sum_{i=1}^{t_1} \left(p_i/P^1\right)^q}{q-1}, \text{ and } S_q^M(t) = \frac{1 - \sum_{i=t_m+1}^{L} \left(p_i/P^M\right)^q}{q-1}, \text{ and } M = m+1 \tag{10}$$

Subject to the following constraints:

$$\left|P^1 + P^2\right| - 1 < S^1 < 1 - \left|P^1 + P^2\right|, \left|P^2 + P^3\right| - 1 < S^2 < 1 - \left|P^2 + P^3\right| \& \left|P^m + P^{m+1}\right| - 1 < S^M < 1 - \left|P^m + P^{m+1}\right| \tag{11}$$

where, P^1, P^2 and P^{m+1} corresponding to S^1, S^2 and S^M have been computed using $t_1, t_2, \dots\dots, t_m$ respectively.

5.2.2 *t*-entropy

A new measure of entropy called t-entropy has been proposed by Chakraborty et al. in the year 2021 [23]. Suppose, an image I associate with normalized histogram $\boldsymbol{p} = (p_0, p_2, p_3, \dots\dots\dots, p_{L-1}) | p_i \geq 0, i = 0, 1, 2, \dots .L-1;$ where L is the number of gray levels in the image I and $\sum_{i=0}^{L-1} p_i = 1$. Then the t-entropy (H_c) of the image is computed as the following expression:

$$H_c(\boldsymbol{p}) = \sum_{i=0}^{L-1} p_i \tan^{-1}\left(\frac{1}{p_i^c}\right) - \frac{\pi}{4} \tag{12}$$

where, c is a positive constant.

Now, if there are $nt = K - 1$ thresholds (t), partitioning the normalized histogram into K classes, then the entropy for each class may be computed as,

$$H_c^1(th_1) = \sum_{i=0}^{th_1-1} \frac{p_i}{w_1} \tan^{-1}\left(\frac{1}{\left(p_i/w_1\right)^c}\right) - \frac{\pi}{4}$$

$$H_c^2(th_2) = \sum_{i=th_1}^{th_2-1} \frac{p_i}{w_2} \tan^{-1}\left(\frac{1}{\left(p_i/w_2\right)^c}\right) - \frac{\pi}{4}$$

⋮
⋮

$$H_c^K(th_{nt}) = \sum_{i=th_{nt}}^{L-1} \frac{p_i}{w_{nt}} \tan^{-1}\left(\frac{1}{\left(p_i/_{w_{nt}}\right)^c}\right) - \frac{\pi}{4} \tag{13}$$

where,

$$w_1(th_1) = \sum_{i=0}^{th_1-1} p_i,\ w_2(th_2) = \sum_{i=th_1}^{th_2-1} p_i, \ldots\ldots\ldots,\ w_K(th_{nt}) = \sum_{i=th_{nt}}^{L-1} p_i \tag{14}$$

where, for ease of computation, two dummy thresholds $th_0 = 0, th_{nt} = L - 1$ are introduced with $th_0 < th_1 < \ldots < th_{n-1} < th_{nt}$. Then the optimum threshold value can be found by

$$\varphi(th_1, th_2, \ldots\ldots, th_{nt}) = Arg\max\left(\left[H_c^1(th_1) + H_c^2(th_2) + \ldots + H_c^K(th_{nt})\right]\right) \tag{15}$$

During the experiment, the positive constant c had been tested over $[0.01, 20]$ and found that $c = 0.1$ is best for multilevel thresholding based image segmentation over the tested datasets.

5.3 Literature Survey on HIOAs Based MLT

Optimization is a methodology of making a design or the system as fully functional as possible that is finely accomplished by a well-tuned algorithm. Nature instead of being fully deterministic is evolutionary, vibrant and resourceful. The nature-inspired algorithms use the best combination and evolution strategy in a given situation However, a new metaheuristic Human-Inspired Optimization Algorithms **(HIOA)** is introduced that uses social behavior in human dynasties. Numerous researchers have advocated quite a lot of optimization approaches wherein a variety of entropy has been exploited as an objective functions. The recent literature of HIOA based MLT has been presented in Table 5. Different parameter's and algorithms abbreviation used in the papers surveyed in Table 3 with its full form is tabularized respectively in Table 6 and Table 7. Total 21 HIOA-MLT papers have been discussed in Table 3 where different papers collected over the years is presented in Fig. 6. Whereas, Fig. 7 indicates the percentage of papers which are surveyed in Table 5 utilizing different types of images.

5.4 Experimental Results and Discussion

This section presents the experimental results that has been computed with the help of six HIOA namely Corona virus Herd Immunity Optimization **(CHIO),** Forensic-Based Investigation Optimization **(FBIO),** Battle Royale Optimization (**BRO**), Political Optimizer **(PO),** Heap-Based Optimizer (**HBO**) and Human Urbanization Algorithm (**HUA**). The result of the six HIOAs considered is further compared with very established Particle Swarm Optimization (**PSO**) algorithm. Further, Tsallis entropy on one hand and t entropy on the other over color satellite images has been considered as an objective functions. The parameters setting of the corresponding methods have been prearranged in Table 8. All seven HIOA have been used in their original versions. Nevertheless, the parameters of each algorithm have been fine-tuned to determine the best values subsequently to produce a good segmentation result within a rational amount of time. In order to do so, a series of experiments has been performed where segmentation is conducted for different threshold numbers and the test images. The value of each parameter has been selected practically (experimentally) with the objective of coming within the reach of the best segmentation. The experimental study includes the evaluation of Tsallis' and t entropy, as objective functions. For the reasonable comparison amongst HIOA methodologies, each execution of the tested objective functions considers the Number of Function Evaluations, $NFE = 1{,}000 * d$, 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 6 and 8 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 HIOA. 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. Each execution of the tested objective functions considers the Number of Function Evaluations, $NFE = 1{,}000*d$, as stopping criterion of the optimization process. For measuring the optimization ability of the HIOAs, mean fitness $\left(\bar{f}\right)$ and standard deviation (σ) have been calculated. On the other hand, segmentation efficiency of the HIOA based models is measured by computing three well known parameters in image segmentation domain i.e. Peak Signal-to-Noise Ratio (PSNR), Feature Similarity Index (FSIM) and Structural Similarity Index (SSIM). MatlabR2018b and Windows-10 OS, $\times$64-based PC, Intel core i5 CPU with 8 GB RAM are the hardware and software requirements incorporated during the experiment. With the intention to verify the efficiency of different NIOA, experiment is conducted using 20 color satellite images. The mentioned algorithms are tried and explored on images extracted from the site of Indian Space Research Organization (ISRO) [24] [https://bhuvan-app1.nrsc.gov.in/imagegallery/bhuvan.html#]. The original color satellite image is shown in Fig. 8.

Table 5 Literature reports on HIOA based multi-level thresholding

SL	Proposed Method	Objective Function	Paper Details	Image Type	Comparison	Quality parameters considered	Observations
1	Imperialist Competitive Algorithm (ICA) for multi-threshold image segmentation	Otsu's and Kapur	Wang et al. in the year **2021** [20]	Standard Gray scale images	ICA with PSO, GWO and TLBO	Maximum and average values of Objective functions, threshold values	The proposed algorithm has quicker convergence speed, superior quality as well as stability in solving multi-threshold segmentation problems as compared to other methods
2	Identification of apple diseases using the Gaining-Sharing Knowledge-Based Algorithm (GSK) for multilevel thresholding	Minimum Cross-Entropy	Ortega et al. in the year **2021** [224]	Standard Color Images	GSK with FFO, PSO, SCA, ABC, HS and DE	PSNR, SSIM and FSIM	The proposed algorithm generates superior quality segmentation compared with other approaches
3	Application of Teaching Learning Based Optimization in Multilevel Image Thresholding	Kapur	Anbazhagan in the year **2021** [108]	Standard Gray scale images	TLBO with SCA, WOA, HHA, SSA, BA, PSO, CSA, and EO	Maximum and average values of Objective functions, threshold values and J-Index	The proposed algorithm is increasingly powerful in finding the global optimal solution for image thresholding issues
4	An efficient method to minimize cross-entropy for selecting multi-level threshold values using an Improved Human Mental Search algorithm (IHMSMLIT)	Minimum Cross-Entropy	Esmaeili in the year **2021** [189]	Standard Gray scale images	IHMSMLIT with PSOMLIT, FAMLIT, BBOMLIT, CSMLIT, GWOMLIT and WOAMLIT	PSNR, SSIM, FSIM and stability analysis	The proposed algorithm obtains best result among the compared algorithms in terms of the quality parameters considered proving the efficacy of the algorithm proposed
5	Medical image segmentation using Exchange Market Algorithm (EMA)	Kapur, Otsu and Minimum Cross Entropy	Sathya et al. in the year **2021** [273]	Medical Images	EMA with KHA, TLBO and CSA	PSNR, and SSIM	The proposed algorithm especially Otsu based EMA method is found to be more accurate and robust for improved clinical decision making and diagnosis
6	Color image segmentation using kapur, otsu and minimum cross entropy functions based on Exchange Market Algorithm	Kapur, Otsu and Minimum Cross Entropy	Sathya et al. in the year **2021** [148]	Standard Color images	EMA with KHA, TLBO and CSA	PSNR, Computational Time and SSIM	The proposed algorithm obtains best result among the compared algorithms and converges quickly than the other algorithms

Table 5 (continued)

SL	Proposed Method	Objective Function	Paper Details	Image Type	Comparison	Quality parameters considered	Observations
7	Multilevel thresholding image segmentation based on improved Volleyball Premier League algorithm using Whale Optimization Algorithm (VPLWOA)	Otsu's	Elaziz et al. in the year **2021** [208]	Standard Gray scale images	VPLWOA with FA, SCA, SSO,VPL and WOA	PSNR, SSIM, RMSE, CPU Time and FSIM	The proposed algorithm outperforms the other algorithms in terms of PSNR, SSIM, and fitness function
8	Image segmentation based on Determinative Brain Storm Optimization (DBSO)	Renyi's and Otsu's	Sovatzidi et al. in the year **2020** [274]	Standard Gray scale images	DBSO with BSO, EMO	Mean PSNR values	The proposed algorithm obtains segmentation results of comparable or higher quality, in less iterations, than the ones obtained by state-of-the-art optimization-based multilevel thresholding methods
9	Human Mental Search (HMS)-based multi-level thresholding for image segmentation	Otsu's and Kapur	Mousavirad et al. in the year **2020** [190]	Standard Gray scale images	HMS with TLBO, BA, FA, PSO, DE and GA	Objective function value, PSNR, SSIM, FSIM, and Curse of dimensionality	The proposed algorithm has better performance than other compared algorithms based on different parameters however, computational time is slightly higher
10	Social-Group-Optimization based tumor evaluation tool for clinical brain MRI of Flair/diffusion-weighted modality (SGO)	Shannon	Dey et al. in the year **2019** [275]	CT and MR Images: Medical Images	No comparison performed	JI, DC, ACC, PRE, SEN, SPE, BCR and BER	The proposed algorithm has acceptable performance generating a Hybrid Image Processing procedure
11	Social Group Optimization and Shannon's Function-Based RGB Image Multi-level Thresholding	Shannon	Monisha et al. in the year **2018** [276]	Standard Color Images	SGO with PSO, BFO, FA, and BA	MSE, PSNR, SSIM, NCC, AD, and SC	The proposed algorithm generates better result compared with the other algorithms considered in this paper
12	Backtracking Search Algorithm for color image multilevel thresholding (MFE-BSA)	Modified Fuzzy Entropy (MFE), Tsalli's	Pare et al. in the year **2018** [223]	Standard Color natural images and Satellite images	MFE-BSA with Energy-Tsalli's-CS, Tsalli's-CS MFE-BFO	PSNR, MSE and CPU Time	The proposed algorithm shows very good segmentation results in terms of preciseness, robustness, and stability

Table 5 (continued)

SL	Proposed Method	Objective Function	Paper Details	Image Type	Comparison	Quality parameters considered	Observations
13	Robust Multi-thresholding in Noisy Grayscale Images Using Otsu's Function and Harmony Search Optimization Algorithm (HSOA)	Otsu's	Suresh et al. in the year **2018** [277]	Standard Gray scale images	No comparison performed	Optimal threshold, PSNR, RMSE	The proposed algorithm with Otsu's function offers promising results. However, it near future, it can be further compared with other heuristic algorithms
14	Hybrid Multilevel Thresholding and Improved Harmony Search Algorithm for Segmentation (MT-IHSA)	Otsu's	Erwin and Saputri in the year **2018** [57]	Standard Gray scale images	MT-IHSA with MT-FA, MT-SSA and Mt-HSA	PSNR	The proposed algorithm with Otsu's function offers high degree of accuracy
15	Jaya Algorithm Guided Procedure to Segment Tumor from Brain MRI	Otsu's	Satapathy et al. in the year **2018** [72]	MR Images: Medical Image	JAYA with FA, TLBO, PSO, BFO, and BA	RMSE, PSNR, SSIM, NCC, AD, SC and CPU Time	The proposed algorithm with Otsu's function offers improved picture excellence measures, image likeness measures, and image statistical measures
16	Robust RGB Image Thresholding with Shannon's Entropy and Jaya Algorithm	Shannon	Maheswari et al. in the year **2018** [9]	General color images	No comparison performed	PQM, RMSE, NCC, SC, NAE, IQM and PSNR	The proposed algorithm with Shannon entropy when applied over normal and noise stained images indicate that the PQM obtained for both the image cases are relatively identical and helps to achieve PSNR values
17	Entropy based segmentation of tumor from brain MR images–Teaching Learning Based Optimization	Kapur, Tsallis and Shannon	Rajinikanth et al. in the year **2017** [278]	MR Images: Medical Image	TLBO-Kapur with TLBO-Shannon and TLBO-Tsallis	PSNR, NCC, NAE, SSIM, PRE, FM, SEN, SPE, BCR, BER, ACC, FPR, FNR, J-Index	The proposed algorithm with Shannon's entropy based thresholding and level set segmentation offers better result for the considered dataset

Table 5 (continued)

SL	Proposed Method	Objective Function	Paper Details	Image Type	Comparison	Quality parameters considered	Observations
18	Parameter-Less Harmony Search (PLHS) for image multi-thresholding	Shannon	Dhal et al. in the year **2017** [54]	General Gray scale images	Eight different variants of PLHS with HS	CT, PSNR, Fit_m and Fit_{std}	The proposed algorithm with lower population size are better for maximizing the Shannon's entropy based objective function with less standard deviation is comparatively better than HS but consumes more computational time when Iteration based stopping criterion is used
19	Otsu and Kapur Segmentation Based on Harmony Search Optimization (HSMA)	Otsu's and Kapur	Cuevas et al. in the year **2016** [56]	Standard Gray scale images	Otsu-HSMA with Kapur-HSMA. GA, PSO and BF	STD, RMSE and PSNR	The proposed algorithm demonstrates outstanding performance, accuracy and convergence in comparison to other methods
20	Multilevel Thresholding Segmentation Based on Harmony Search Optimization (HSMA)	Otsu's and Kapur	Oliva et al. in the year **2013** [55]	Standard Gray scale images	Otsu-HSMA with Kapur-HSMA. GA, PSO and BF	PSNR, STD, mean of the objective function values	The proposed algorithm demonstrates the high performance for the segmentation of digital images as compared to other algorithms considered in the paper
21	Image thresholding optimization based on Imperialist Competitive Algorithm	Otsu's	Razmjooy et al. in the year **2011** [279]	Standard Gray scale images	ICA with GA	MSE and PSNR	The proposed algorithm demonstrates the good performance and generated acceptable result

Table 6 Different qualitative parameters mentioned in the paper surveyed in Table 5 and its full form

Parameter used	Abbreviations	Parameter used	Abbreviations
Peak Signal-to-Noise Ratio	PSNR	Jaccard-Index	J-Index
Normalized Cross-Correlation	NCC	Mean Fitness value	Fitm
Normalized Absolute Error	NAE	Standard Deviation	Fitstd
Structural Similarity Index	SSIM	Computational Time	CT
Precision	PRE	Root Mean Square Error	RMSE
F-Measure	FM	Standard Deviation	STD
Sensitivity	SEN	Structural Content	SC
Specificity	SPE	Average Difference	AD
Balanced Classification Rate	BCR	Picture-Quality-Measures	PQM
Balanced Error Rate	BER	Normalized Absolute Error	NAE
Accuracy	ACC	Image Quality Measure	IQM
False Positive Rate	FPR	Jaccard Coefficient	JC
False Negative Rate	FNR	Dice Coefficient	DC

Table 7 Different algorithms mentioned in the paper surveyed in Table 5 and its full form

Name of the algorithm	Abbreviations	Name of the algorithm	Abbreviations
Particle Swarm Optimization	PSO	Determinative Brain Storm Optimization	DBSO
Gray Wolf Optimization	GWO	Parameter Less Harmony Search	PLHS
Cuckoo Search Algorithm	CSA	Harmony Search Optimization Algorithm	HSOA
Harmony Search	HS	Multilevel Thresholding Improved Harmony Search Algorithm	MT-IHSA
Whale Optimization Algorithm	WOA	Multilevel Thresholding Salp Swarm Algorithm	MT-SSA
Sine Cosine Algorithm	SCA	Multilevel Thresholding Firefly Algorithm	MT-FA
Volleyball Premier League	VPL	Multilevel Thresholding Harmony Search Algorithm	MT-HSA
Salp Swarm Algorithm	SSA	Harmony Search Multilevel Thresholding Algorithm	HSMA
Bat Algorithm	BA	Teaching–Learning Based Optimization	TLBO
Crow Search Algorithm	CSA	Harris Hawks Optimization Algorithm	HHA
Equilibrium Optimizer	EO	Bacterial Foraging Optimization	BFO
Brain Storm Optimization	BSO	Improved Human Mental Search Multi Level Image Thresholding	IHMSMLIT
Genetic Algorithm	GA	Particle Swarm Optimization Multi Level Image Thresholding	PSOMLIT
Exchange Market Algorithm	EMA	Firefly Algorithm Multi Level Image Thresholding	FAMLIT
Human Mental Search	HMS	Biogeography Based Optimization Multi Level Image Thresholding	BBOMLIT
Genetic Algorithm	GA	Cuckoo Search Multi Level Image Thresholding	CSMLIT
Differential Evolution	DE	Gray Wolf Optimization Multi Level Image Thresholding	GWOMLIT
Firefly Algorithm	FA	Whale Optimization Algorithm Multi Level Image Thresholding	WOAMLIT
Krill herd Algorithm	KHA	Modified Fuzzy Entropy Backtracking Search Algorithm	MFE-BSA
Gravitational Search Algorithm	GSA	Electro Magnetism-like Optimization	EMO
Fire Fly Optimizer	FFO	Whale Optimization Algorithm	WOA
Artificial Bee Colony	ABC	Volleyball Premier League Whale Optimization Algorithm	VPLWOA
Social-Group-Optimization	SGO	Spherical Search Optimizer	SSO
Backtracking Search Algorithm	BSA	Gaining Sharing Knowledge-Based Algorithm	GSK
Bacterial Foraging	BF	Imperialist Competitive Algorithm	ICA
Cuckoo Search	CS		

5.4.1 Results Over Tsallis Entropy for Color Satellite Image

Figure 9 highlights the visual segmented results of the original image of Fig. 8 using six different HIOA (PO, CHIO, HBO, FBIO, BRO and HUA) which is further compared with one of the popular algorithm i.e. PSO with Tsallis entropy as objective function over 6 and 8 thresholds for a color satellite image. Table 9 projects numerical comparison of various aforesaid HIOA with Tsallis entropy as objective function over 6 and 8 thresholds for the satellite image

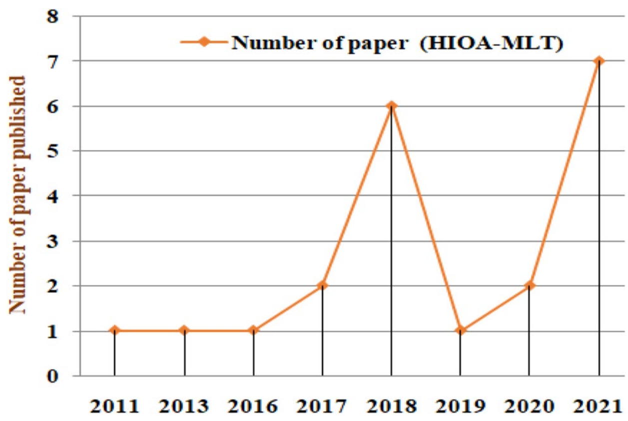

Fig. 6 Number of HIOA-MLT based paper published over years

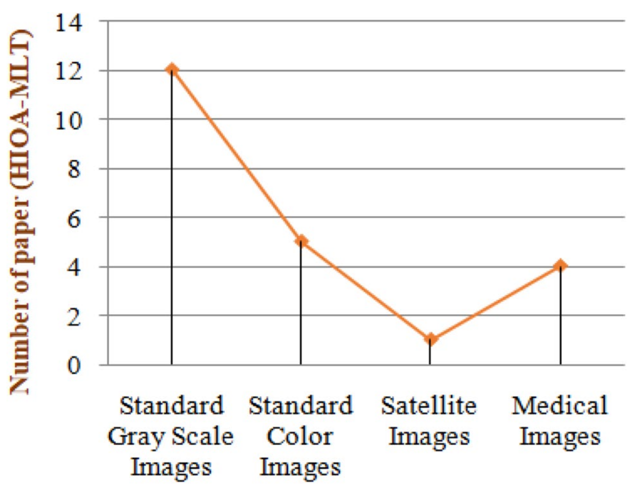

Fig. 7 Number of surveyed HIOA-MLT paper as per types of images

considering numerous parameters such as fitness function $\left(\bar{f}\right)$, standard deviation (σ_f), Computational time (Time (sec)), FSIM, PSNR and SSIM. Additionally, the entries that are highlighted in boldface indicate the best performance results. Table 9 clearly bring to light that PO accomplishes the best result over the threshold value (nt = 6) for every parameters taken into account while PSO bestows the worst end result when compared amongst all the six tested HIOAs. Further, for thresholds value (nt = 8) for parameters namely $\left(\bar{f}\right)$, Time (sec), FSIM, PSNR and SSIM, PO exhibits the best result whereas HUA attains the best value in terms of (σ_f). On the other hand for the same threshold value, yet again PSO bestows the worst end result when compared amongst all the six tested HIOAs. The fitness value of PO is judged against other six HIOAs and PSO considered. A non-parametric significance proof known as Wilcoxon's rank test has been performed wherein such proof authorizes to estimate differences in the result amid two associated methods. 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 10 tabulates the pair-wise comparison among HIOA (PO vs. CHIO; PO vs. HBO; PO vs. FBIO; PO vs. BRO; and PO vs. PSO) depending on Wilcoxon p-values over Satellite image for Tsallis entropy for 6 and 8 number of thresholds. All the Wilcoxon p-values obtained and thereby projected in Table 10 are less than 0.05 (5% significance level) with $h = 1$ is an apparent proof not in favor of the null hypothesis, inferring that the PO fitness values for the performance are statistically superior. This further indicates that PO in amalgamation with Tsallis entropy as objective function is proficient enough to bring into being consistent solution irrespective of the threshold values as in all the cases of comparison for both nt = 6 and 8 value of $p < 0.05$ and $h = 1$.

5.4.2 Results Over t- Entropy for Color Satellite Image

Figure 10 highlights the visual segmented results of the original image of Fig. 8 using six different HIOA (PO, CHIO, HBO, FBIO, BRO and HUA) which is further compared with one of the popular algorithm i.e. PSO with t-entropy as objective function over 6 and 8 thresholds for a satellite image. Table 11 projects numerical comparison of various aforesaid HIOA with t-entropy as objective function over 6 and 8 thresholds for the satellite image considering numerous parameters such as fitness function $\left(\bar{f}\right)$, standard deviation (σ_f), Computational time (Time (sec)), FSIM, PSNR and SSIM. Additionally, the entries that are highlighted in boldface indicate the best performance results. Table 11 clearly bring to light that PO accomplishes the best result over the threshold value (nt = 6) for every parameters taken into account except for (σ_f) wherein CHIO attains the best (σ_f) value. PSO bestows the worst end result when compared amongst all the six tested HIOAs. It is to be noted that for the same threshold value i.e. nt = 6, HUA in regard to fitness function $\left(\bar{f}\right)$ attains the same value as that of PSO. Further, for thresholds value (nt = 8) for the entire parameters, PO exhibits the best result. On the other hand for the same threshold value, yet again PSO bestows the worst end result when compared amongst all the six tested HIOAs for parameters fitness function $\left(\bar{f}\right)$, Computational time (Time (sec)), FSIM, PSNR and SSIM whereas BRO attains the worst value for standard deviation (σ_f). The fitness value of PO is judged against other six HIOAs and PSO considered. A non-parametric significance proof known as Wilcoxon's rank test has been performed wherein such proof authorizes to estimate differences in the result amid two

Table 8 Parameter setting of HIOAs

Algorithms	Parameters	Description	Value initialized
Corona virus Herd Immunity Optimization (**CHIO**)	C_0	Number of initial infected case	1
	Max_Itr	Maximum number of iterations	1000
	HIS	Population Size	50
	BR_r	Basic Reproduction Rate	0.01
	Max_{Age}	Maximum age of the infected cases	100
	HIP	Herd Immunity Population	[0 or 1]
	R	Random Number	[0,1]
	A_j	Age Vector	1
	S_j	Status Vector	1
Forensic-Based Investigation Optimization (**FBIO**)	N	Population Size	50
	rand	Random Number	[–1,1]
	rand_1	Random Number	[0,1]
	rand_2	Random Number	[0,1]
	A	Effectiveness coefficient	[–1,1]
Political Optimizer (**PO**)	*N*	Number of parties, constituencies, and members in each party	5
	T_{max}	Total number of iterations	500
	r	Random Number	[0,1]
	ƛ	party switching rate	1
Battle Royale Optimization (**BRO**)	*iter*	Maximum number of iterations	500
	Population_size	Population Size	50
	Threshold	Threshold	3
	r	Random Number	[0,1]
Heap-Based Optimizer (**HBO**)	*T*	Maximum number of iterations	500
	r	Random Number	[0,1]
	p	Random Number	[0,1]
	N	Size of Population	50
	D	Number of Dimension (variables)	30
	C	Number of Cycles (c = T/25)	8
Human Urbanization Algorithm (**HUA**)	*t*	Number of Iterations	500
	R	Random Number	[0,1]
	R^i	Random Number	[–1,1]
	K	Controlling diversification and intensification of adventurers	2
	Ripmk	Balancing between diversification and intensification in searching the city's boundaries	1
	N	Population Size	50
Particle Swarm Optimization (**PSO**)	C_1	Acceleration coefficients	2
	C_2	Acceleration coefficients	2
	n	Population Size	50

associated methods. 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 12 tabulates the pair-wise comparison among HIOA (PO vs. CHIO; PO vs. HBO; PO vs. FBIO; PO vs. BRO; and PO vs. PSO) depending on Wilcoxon *p*-values over Satellite image for t-entropy for 6 and 8 number of thresholds. All the Wilcoxon *p*-values obtained and thereby projected in Table 11 are less than 0.05 (5% significance level) with $h = 1$ is an apparent proof not in favor of the null hypothesis, inferring that the PO fitness values for the performance are statistically superior. However, Table 11 additionally indicates that PO in amalgamation with t-entropy as objective function is proficient enough to bring into being consistent solution when the threshold value (nt = 8) however, as its clear from the table

Fig. 8 Original color satellite image (Input Image)

that when the threshold value (nt = 6), there is no significant difference (as $p > 0.05$ and $h = 0$) between PO and few HIOAs namely CHIO. HBO, FBIO and BRO but PO outperforms HUA and PSO as depicted by the value of p and h (as $p < 0.05$ and $h = 1$).

5.4.3 Discussion on the Performance Comparison Among Different Objective Functions Employed

From the values obtained for different parameters in the tables highlighted above (Tables 9 and 11), it is evident that on comparing different HIOA's for the satellite images using two prominent objective functions namely Tsallis and *t*-entropy for different threshold values ($nt = 6$ and 8), Tsallis entropy outperforms for every HIOA's as well as PSO over parameters such as fitness function $\left(\bar{f}\right)$, standard deviation (σ_f), Computational time (Time (sec)), FSIM, PSNR as well as SSIM. It is noteworthy to highlight that different HIOA's generates high fitness values for all threshold values considering Tsallis entropy to segment the standard color images as compared to segmentation using *t*-entropy as an objective function. Further, it can be deduced and inferred from the experimental outcome that every HIOAs in combination with Tsallis entropy outperforms the HIOA combination with *t*-entropy in almost all cases and almost all parameters taken into consideration. On the other hand, considering Tables 10 and 12, it is apparent that for every parameter considered in the scenario, every HIOA's in combination with Tsallis entropy generates better result and proves superior to that of HIOA combined with *t*-entropy as an objective function for every threshold values. This surely indicates that though *t*-entropy is the newly introduced concept rarely

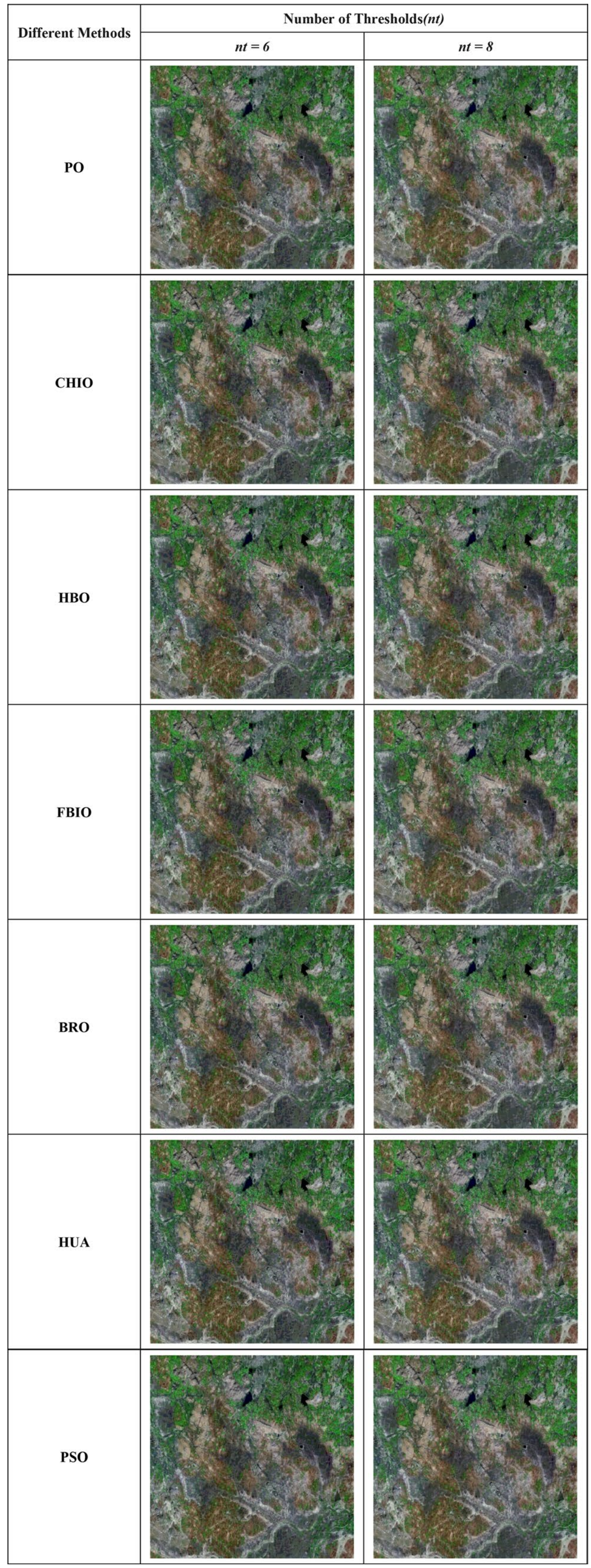

Fig. 9 Segmented results of different HIOAs using Tsallis entropy over *nt = 6 and 8*

Table 9 Numerical comparison of HIOA for Tsallis entropy as objective function over satellite image

Number of thresholds (nt)	HIOA	$\bar{f}$	σ_f	Time (sec.)	FSIM	PSNR	SSIM
6	PO	**3146969.68**	**1.18E-12**	**4.0438**	**0.9898**	**22.89**	**0.8897**
	CHIO	3146863.76	3.11E-11	4.1522	0.9897	22.77	0.8884
	HBO	3146853.55	4.01E-12	4.1601	0.9895	22.68	0.8882
	FBIO	3146841.29	2.57E-11	4.2011	0.9892	22.65	0.8881
	BRO	3146824.68	3.78E-12	4.2009	0.9891	22.61	0.8879
	HUA	3146811.89	4.82E-11	4.3221	0.9886	22.59	0.8875
	PSO	3146804.84	3.13E-11	4.3225	0.9884	22.51	0.8871
8	PO	**79224340.77**	1.70E-11	**5.1361**	**0.9955**	**25.32**	**0.9299**
	CHIO	79213418.64	1.58E-11	5.3354	0.9951	25.18	0.9294
	HBO	79213017.45	**1.34E-11**	5.3558	0.9948	25.14	0.9291
	FBIO	79212899.89	5.27E-11	5.4004	0.9945	25.10	0.9286
	BRO	79212575.77	2.42E-10	5.4001	0.9942	25.04	0.9282
	HUA	79212455.74	2.37E-11	5.5019	0.9938	24.99	0.9278
	PSO	79212244.52	3.45E-10	5.5022	0.9932	24.95	0.9275

Best results are highlighted in bold

Table 10 Comparison among HIOA depending on Wilcoxon p-values over satellite image for Tsallis entropy

Pair of HIOA	Tsallis entropy over standard color image			
	$nt=6$		$nt=8$	
	p	h	p	h
PO vs. CHIO	<0.05	1	<0.05	1
PO vs. HBO	<0.05	1	<0.05	1
PO vs. FBIO	<0.05	1	<0.05	1
PO vs. BRO	<0.05	1	<0.05	1
PO vs. HUA	<0.05	1	<0.05	1
PO vs. PSO	<0.05	1	<0.05	1

employed in image segmentation, Tsallis entropy as an objective function presents an interesting and unconventional choice for satellite image segmentation task and further, same has been clearly highlighted in Fig. 11a, b, c and d. In addition, the another analysis made from the above mentioned tables is that as the number of threshold enhances computational time increases no doubt but values for FSIM, PSNR and SSIM also amplify for the objective function considered under this scenario.

6 Conclusion and Future Research Directions

Amongst the list of algorithms instigated and existing in literature, deciding upon an algorithm entails not just a meticulous understanding of its theoretical fundamentals but also require systematically comprehending upon the different components of algorithm along with its different parameters and application areas. This work attempted and strived towards concentrating on these issues and talks about pertinent conceptions related to HIOAs such as components, classification, common structure, application areas, work carried out till date and many more. A number of optimization technique inspired from human behavior and intelligence for MLT color satellite image segmentation problem considering two significant objective functions i.e. Tsallis' and t-entropy has been discussed in this paper. To reveal the connotation of HIOAs in the field of MLT image segmentation six different algorithms namely Corona virus Herd Immunity Optimization **(CHIO),** Forensic-Based Investigation Optimization **(FBIO),** Battle Royale Optimization (**BRO**), Political Optimizer **(PO),** Heap-Based Optimizer (**HBO**) and Human Urbanization Algorithm (**HUA**) has been implemented and further compared among themselves and with one of the popular Swarm based optimization algorithm i.e. Particle Swarm Optimization (**PSO**). The comparison is made taking into account numerous parameters such as fitness function $\left(\bar{f}\right)$, standard deviation $\left(\sigma_f\right)$, Computational time (Time (sec)), FSIM, PSNR and SSIM based on the evaluation of two predominant objective function as revealed earlier (Tsallis' and t-entropy). The results and contribution of this paper have been summarized as follows:

(a) The numerical outcome demonstrates that Political Optimizer **(PO)** confirmed and exhibited its competence and accuracy over other HIOA's (as depicted in **Sect. 5.4**) and PSO signifying that PO is most suitable HIOA for MLT image segmentation process of color

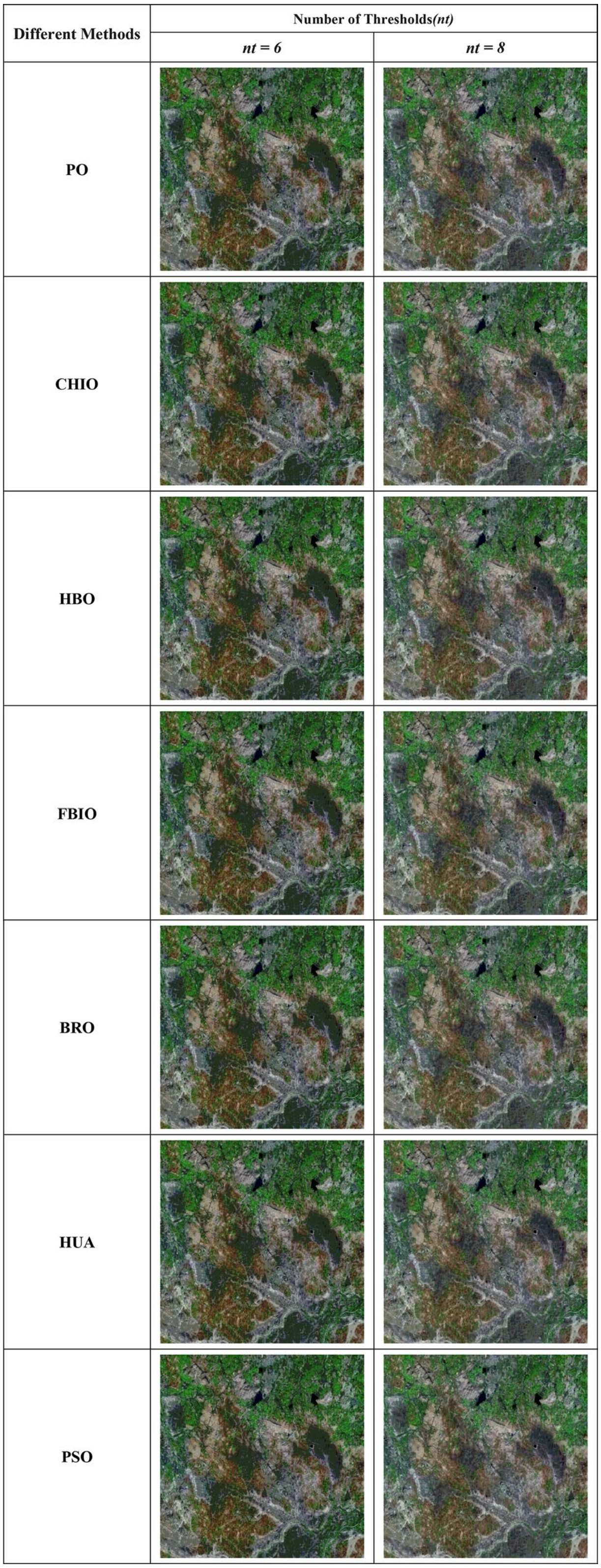

Fig. 10 Segmented results of different HIOAs using t- entropy over *nt* = *6 and 8*

satellite image with Tsallis' entropy as objective function.

(b) Though *t*-entropy as the objective function is the recently introduced and rarely employed in image segmentation, Tsallis entropy as an objective function under different circumstances provides an attention-grabbing result and thus can be an eccentric preference for satellite image segmentation task.

(c) Both objective functions considered in this paper in connection with different HIOA are though suitable for color satellite image segmentation however, result of *t*-entropy as the objective function is dependent on the threshold value.

(d) Lastly as mentioned earlier, it is to be noted that as the number of threshold increases, values for FSIM, PSNR and SSIM also intensifies for both of the objective function considered under this scenario. Also, with tsallis entropy as objective function, different HIOAs as well as PSO considered for the experimental purpose generated high fitness values irrespective of threshold values considered.

No doubt, HIOAs have evidently proved itself as an effective mechanism to unravel intricate real-world optimization problems; it can still be further explored. With this, few research directions has been projected below that shall hopefully turn out to be useful for the researcher to excavate and discover HIOAs further.

(a) Proficient but less obscure HIOA (lesser number of operators, tuning parameters etc.) is the need of an hour. Parameterless HIOAs can be good work in future [25, 26].

(b) Development of HIOAs based image clustering especially histogram based image clustering should an emergent research topic [27–30]

(c) Exploring and analyzing each HIOAs that fits the best for the problem one intend to resolve at times is not just tiresome but also not realistic so more parameters need to be identified to classify HIOAs making it easier for the researcher to select the suitable one.

(d) From the above table i.e. Table 5 that highlights the literature review of HIOA on MLT domain undoubtedly point out that maximum HIOAs has been employed for MLT image segmentation for standard gray scale images (Fig. 7) however, very less work has been performed for satellite images, medical images and even standard color images. Exploring and applying HIOAs over these variant of images could be a good work.

(e) Also, Table 5 brings to lights the usage of different objective functions, wherein maximum work has been done with Otsu and Kapur as objective functions. Exploring more of the existing objective function and

Table 11 Numerical comparison of HIOA for *t*-entropy as objective function over satellite image

Number of thresholds (*nt*)	HIOAs	$\bar{f}$	σ_f	Time (sec.)	FSIM	PSNR	SSIM
6	PO	**0.893337**	3.89E-20	**5.4789**	**0.9619**	**18. 94**	**0.7868**
	CHIO	0.893336	**1.02E-21**	5.4997	0.9618	18.92	0.7866
	HBO	0.893336	1.39E-21	5.5004	0.9618	18.90	0.7865
	FBIO	0.893336	8.36E-20	5.5858	0.9615	18.75	0.7864
	BRO	0.893336	1.24E-20	5.6151	0.9611	18.74	0.7862
	HUA	0.893335	1.59E-21	6.0044	0.9599	18.67	0.7859
	PSO	0.893335	1. 58E-20	6.1117	0.9589	18.59	0.7853
8	PO	**1.166417**	**5.66E-21**	**6.6935**	**0.9891**	**22. 99**	**0.8961**
	CHIO	1.166384	5.28E-20	6.7125	0.9888	22. 69	0.8958
	HBO	1.166377	4.42E-20	6.7211	0.9885	22.61	0.8955
	FBIO	1.166368	1.76E-20	6.7455	0.9881	22.59	0.8954
	BRO	1.166361	7.98E-20	6.7401	0.9879	22.55	0.8951
	HUA	1.166343	7.81E-20	7.1012	0.9875	22.49	0.8948
	PSO	1.166315	1.13E-20	7.1113	0.98471	22.41	0.8945

Best results are highlighted in bold

Table 12 Comparison among HIOA depending on Wilcoxon *p*-values over satellite image for *t*-entropy

Pair of HIOA	*t*-entropy over standard color image			
	nt = 6		*nt* = 8	
	p	*h*	*p*	*h*
PO vs. CHIO	>0.05	0	<0.05	1
PO vs. HBO	>0.05	0	<0.05	1
PO vs. FBIO	>0.05	0	<0.05	1
PO vs. BRO	>0.05	0	<0.05	1
PO vs. HUA	<0.05	1	<0.05	1
PO vs. PSO	<0.05	1	<0.05	1

applying the same or applying Two-Dimensional (2D) objective functions like 2D Otsu, 2D Tsallis, 2D-Renyi, 2D Cross etc., over diverse HIOAs in MLT domain could be interesting as well as challenging.

(f) Hybridization and parallel models has always proved efficient and could be a great future research. In this regard, hybridization [31] of for instance Social Learning Optimization inspired Archimedes Optimization Algorithm or a novel PSO model based on Simulating Cohort Intelligence. Recently human intelligences or human social communication based PSO models are developed and provided outstanding results [15, 32, 33].

(g) Though *t*-entropy generated acceptable result, however, it could not be proved commendable when compared with the other objective functions under similar circumstances. Consequently, improvised variant of t-entropy could be a good work.

(h) Initial parameters are heuristically assumed so there is always a scope to find a specific / standard method to fix, control and tune the initial parameters. This could be looked upon. Introducing novel performance measures to evaluate the success of an algorithm is also a necessity.

(i) Lastly, inspiration taken from behavior of quantum particles to develop metaheuristic optimization algorithms [34] is as well gaining popularity and applied in numerous application domain. In this perspective, introducing a quantum inspired HIOA could be a great research work that can be conducted in future.

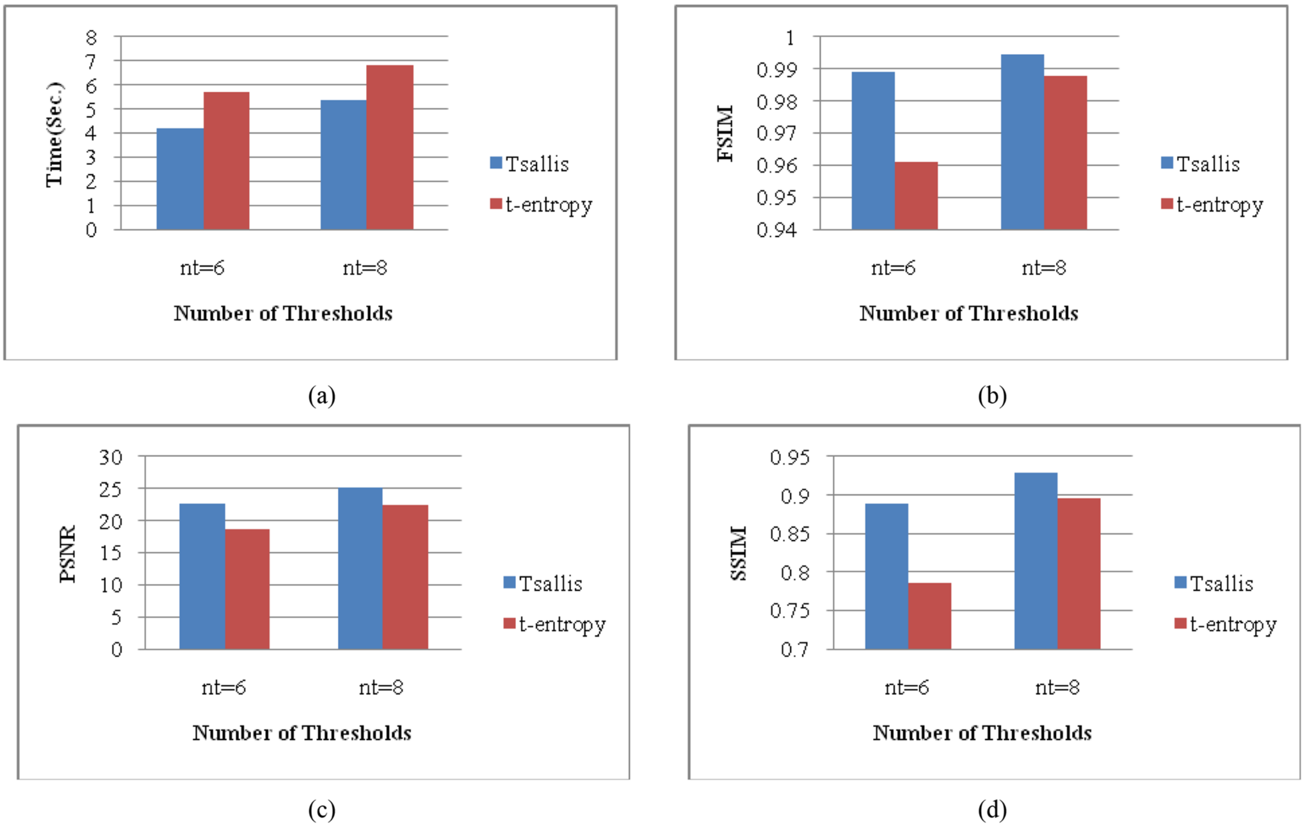

Fig. 11 Comparison among Tsallis and *t*-entropy over Color Satellite Images

Funding There is no funding related to this research.

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.

References

1. Zhang H, Zhou J, Zhang Y, Lu Y, Wang Y (2013) Culture belief based multi-objective hybrid differential evolutionary algorithm in short term hydrothermal scheduling. Energy Convers Manage 65:173–184
2. Baykasoğlu A, Hamzadayi A, Köse SY (2014) Testing the performance of teaching–learning based optimization (TLBO) algorithm on combinatorial problems: flow shop and job shop scheduling cases. Inf Sci 276:204–218
3. Sun X, Zhang Y, Ren X, Chen K (2015) Optimization deployment of wireless sensor networks based on culture–ant colony algorithm. Appl Math Comput 250:58–70
4. Chen J, Cheng S, Chen Y, Xie Y, Shi Y (2015) Enhanced brain storm optimization algorithm for wireless sensor networks deployment. In: Tan Ying et al (eds) International conference in swarm intelligence. Springer, Cham, pp 373–381
5. Askari Q, Younas I (2021) Improved political optimizer for complex landscapes and engineering optimization problems. Expert Syst Appl 182:115178
6. Kashan AH (2011) An efficient algorithm for constrained global optimization and application to mechanical engineering design: league championship algorithm (LCA). Comput Aided Des 43(12):1769–1792
7. Tuba E, Strumberger I, Zivkovic D, Bacanin N, Tuba, M (2018) Mobile robot path planning by improved brain storm optimization algorithm. In 2018 IEEE congress on evolutionary computation (CEC) (pp. 1–8). IEEE.
8. Huang L, Duan H, Wang Y (2014) Hybrid bio-inspired lateral inhibition and imperialist competitive algorithm for complicated image matching. Optik 125(1):414–418
9. Maheswari B, Mohanapriya N, Raja NSM (2018) Robust RGB image thresholding with Shannon's entropy and Jaya algorithm. In 2018 IEEE international conference on system, computation, automation and networking (ICSCA) (pp. 1–5). IEEE.

10. Zhang M, Jiang W, Zhou X, Xue Y, Chen S (2019) A hybrid biogeography-based optimization and fuzzy C-means algorithm for image segmentation. Soft Comput 23(6):2033–2046
11. Ameur M, Habba M, Jabrane Y (2019) A comparative study of nature inspired optimization algorithms on multilevel thresholding image segmentation. Multimedia Tools App 78(24):34353–34372
12. Rai R, Das A, Dhal KG (2022) Nature-inspired optimization algorithms and their significance in multi-thresholding image segmentation: an inclusive review. Evol Syst. https://doi.org/10.1007/s12530-022-09425-5
13. Dhal KG, Das A, Ray S, Gálvez J, Das S (2020) Nature-inspired optimization algorithms and their application in multi-thresholding image segmentation. Arch Comput Methods Eng 27(3):855–888
14. Kumar A, Nadeem M, Banka H (2022) Nature inspired optimization algorithms: a comprehensive overview. Evolv Syste. https://doi.org/10.1007/s12530-022-09432-6
15. Liu Y, Niu B (2012) A novel PSO model based on simulating human social communication behavior. Discrete Dyn Nat Soc 2012:1–21
16. Yang XS (2020) Nature-inspired optimization algorithms: challenges and open problems. J Comput Sci 46:101104
17. Xing Z, Jia H (2020) An improved thermal exchange optimization based GLCM for multi-level image segmentation. Multimedia Tools App. https://doi.org/10.1007/s11042-019-08566-1
18. Chatterjee A, Siarry P, Nakib A, Blanc R (2012) An improved biogeography based optimization approach for segmentation of human head CT-scan images employing fuzzy entropy. Eng Appl Artif Intell 25(8):1698–1709
19. Xing Z, Jia H (2020) Modified thermal exchange optimization based multilevel thresholding for color image segmentation. Multimedia Tools App 79(1):1137–1168
20. Wang M, Pan G, Liu Y (2019) A novel imperialist competitive algorithm for multithreshold image segmentation. Math Problems Eng 2019:1–18
21. Pare S, Kumar A, Singh GK, Bajaj V (2020) Image segmentation using multilevel thresholding: a research review. Iran J Sci Technol Trans Electric Eng 44(1):1–29
22. Ray S, Parai S, Das A, Dhal KG, Naskar PK (2022) Cuckoo search with differential evolution mutation and Masi entropy for multi-level image segmentation. Multimedia Tools App 81(3):4073–4117
23. Chakraborty S, Paul D, Das S (2021) t-entropy: a new measure of uncertainty with some applications. arXiv preprint arXiv:2105.00316.
24. Dhal KG, Ray S, Das A, Gálvez J, Das S (2019) Fuzzy multilevel color satellite image segmentation using nature-inspired optimizers: a comparative study. J Indian Soc Remote Sens 47(8):1391–1415
25. Dhal KG, Sahoo S, Das A, Das S (2020) Effect of population size over parameter-less firefly algorithm. In: Dey N (ed) Applications of firefly algorithm and its variants. Springer, Singapore, pp 237–266
26. Ghosal D, Das A, Dhal KG (2022) A comparative study among clustering techniques for leaf segmentation in rosette plants. Pattern Recognit Image Anal 32(1):129–141
27. Dhal KG, Das A, Ray S, Gálvez J (2021) Randomly attracted rough firefly algorithm for histogram based fuzzy image clustering. Knowl-Based Syst 216:106814
28. Das A, Dhal KG, Ray S, Gálvez J (2022) Histogram-based fast and robust image clustering using stochastic fractal search and morphological reconstruction. Neural Comput Appl 34(6):4531–4554
29. Dhal KG, Gálvez J, Ray S, Das A, Das S (2020) Acute lymphoblastic leukemia image segmentation driven by stochastic fractal search. Multimedia Tools Appl 79(17):12227–12255
30. Dhal KG, Das A, Ray S, Sarkar K, Gálvez J (2021) An analytical review on rough set based image clustering. Arch Comput Methods Eng, 1–30.
31. Moghdani R, Elaziz MA, Mohammadi D, Neggaz N (2021) An improved volleyball premier league algorithm based on sine cosine algorithm for global optimization problem. Eng Comput 37(4):2633–2662
32. Tanweer MR, Sundaram S (2014) Human cognition inspired particle swarm optimization algorithm. In 2014 IEEE ninth international conference on intelligent sensors, sensor networks and information processing (ISSNIP) (pp. 1–6). IEEE.
33. Tanweer MR, Al-Dujaili A, Suresh S (2015) Empirical assessment of human learning principles inspired PSO algorithms on continuous black-box optimization testbed. In: Panigrahi BK et al (eds) International conference on swarm, evolutionary, and memetic computing. Springer, Cham, pp 17–28
34. Alvarez-Alvarado MS, Alban-Chacon FE, Lamilla-Rubio EA, Rodriguez-Gallegos CD, Velásquez W (2021) Three novel quantum-inspired swarm optimization algorithms using different bounded potential fields. Sci Rep 11(1):1–22
35. Reynolds RG (1994) An introduction to cultural algorithms. Proc Third Ann Conf Evol Program 24:131–139
36. Liu J, Gao H, Zhang J, Dai B (2007, December). Urban power network substation optimal planning based on geographic culture algorithm. In 2007 international power engineering conference (IPEC 2007) (pp. 500–504). IEEE.
37. Chen B, Zhao L, Lu JH (2009, April). Wind power forecast using RBF network and culture algorithm. In 2009 international conference on sustainable power generation and supply (pp. 1–6). IEEE.
38. Verma HK, Singh P (2018) Optimal reconfiguration of distribution network using modified culture algorithm. J Instit Eng B 99(6):613–622
39. Vafaei A, Ghaedi AM, Avazzadeh Z, Kiarostami V, Agarwal S, Gupta VK (2021) Removal of hydrochlorothiazide from molecular liquids using carbon nanotubes: radial basis function neural network modeling and culture algorithm optimization. J Mol Liq 324:114766
40. Si-hua C (2012) A novel culture algorithm and it's application in knowledge integration. Int Inform Instit 15(11):4847
41. Chen SH, Tao CQ (2009) New knowledge integration strategy based on culture algorithm framework [J]. J Chinese Comput Syst 30(10):2030–2033
42. Naitali A, Giri F (2010, June). Wiener and Hammerstein nonlinear systems identification using hybrid genetic and swarming intelligence based culture algorithm. In Proceedings of the 2010 American control conference (pp. 4528–4533). IEEE.
43. Chen X, Zhang L, Zhang Z (2020) An integrated model for maintenance policies and production scheduling based on immune–culture algorithm. Proc Instit Mech Eng, Part O 234(5):651–663
44. Liu S, Yang D, Ge C, Huang W (2021, July). Research on fault-tolerant scheduling of precedent tasks based on primary/backup and culture algorithm. In 2021 IEEE international conference on power, intelligent computing and systems (ICPICS) (pp. 445–449). IEEE.
45. Guo YN, Xiao D, Zhang S, Cheng J (2011) Multi-spectral remote sensing images classification method based on adaptive immune clonal selection culture algorithm. In: Huang D-S et al (eds) International conference on intelligent computing. Springer, Berlin, Heidelberg, pp 319–326

46. Meng FR, Hao XY, Zhou Y (2009) Selective neural network ensemble approach based on cultural algorithm. J Chinese Comput Syst 5:933–936
47. Guang-jun, YANG (2012). Mining association rules based on immune clone culture algorithm. Comput Eng Sci, 3.
48. Zhou J, Bai T, Suo C (2008, August). The SVM optimized by culture genetic algorithm and its application in forecasting share price. In 2008 IEEE international conference on granular computing (pp. 838–843). IEEE.
49. Geem ZW, Kim JH, Loganathan GV (2001) A new heuristic optimization algorithm: harmony search. Simulation 76(2):60–68
50. Yıldız AR (2008) Hybrid Taguchi-harmony search algorithm for solving engineering optimization problems. Int J Ind Eng 15(3):286–293
51. Asad A, Deep K (2016) Applications of harmony search algorithm in data mining a survey. In Pant, M. et al. (Eds.), Proceedings of fifth international conference on soft computing for problem solving. Springer: Singapore, pp 863–874.
52. Degertekin SO (2008) Optimum design of steel frames using harmony search algorithm. Struct Multidiscip Optim 36(4):393–401
53. Manjarres D, Landa-Torres I, Gil-Lopez S, Del Ser J, Bilbao MN, Salcedo-Sanz S, Geem ZW (2013) A survey on applications of the harmony search algorithm. Eng Appl Artif Intell 26(8):1818–1831
54. Dhal KG, Fister Jr I, Das S (2017, October). Parameterless harmony search for image multi-thresholding. In 4th student computer science research conference (StuCosRec-2017) (pp. 5–12).
55. Oliva D, Cuevas E, Pajares G, Zaldivar D, Perez-Cisneros M (2013) Multilevel thresholding segmentation based on harmony search optimization. J Appl Math, 2013.
56. Cuevas E, Zaldívar D, Perez-Cisneros M (2016) Otsu and Kapur segmentation based on harmony search optimization. In Applications of evolutionary computation in image processing and pattern recognition (pp. 169–202). Springer, Cham.
57. Erwin S, Saputri W (2018) Hybrid multilevel thresholding and improved harmony search algorithm for segmentation. Int J Electric Comput Eng (IJECE) 8(6):4593–4602
58. Ray T, Liew KM (2003) Society and civilization: an optimization algorithm based on the simulation of social behavior. IEEE Trans Evol Comput 7(4):386–396
59. Dai C, Zhu Y, Chen W (2006, November) Seeker optimization algorithm. In International conference on computational and information science (pp. 167–176). Springer, Berlin, Heidelberg.
60. Dai C, Chen W, Zhu Y (2009) Seeker optimization algorithm for digital IIR filter design. IEEE Trans Industr Electron 57(5):1710–1718
61. Dai C, Chen W, Zhu Y, Zhang X (2009) Seeker optimization algorithm for optimal reactive power dispatch. IEEE Trans Power Syst 24(3):1218–1231
62. Shaw B, Mukherjee V, Ghoshal SP (2012) Solution of economic dispatch problems by seeker optimization algorithm. Expert Syst Appl 39(1):508–519
63. Zhu Y, Dai C, Chen W (2014) Seeker optimization algorithm for several practical applications. Int J Comput Intell Syst 7(2):353–359
64. Atashpaz-Gargari E, Lucas C (2007, September). Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition. In 2007 IEEE congress on evolutionary computation (pp. 4661–4667). IEEE.
65. Hadidi A, Hadidi M, Nazari A (2013) A new design approach for shell-and-tube heat exchangers using imperialist competitive algorithm (ICA) from economic point of view. Energy Convers Manage 67:66–74
66. Lucas C, Nasiri-Gheidari Z, Tootoonchian F (2010) Application of an imperialist competitive algorithm to the design of a linear induction motor. Energy Convers Manage 51(7):1407–1411
67. Niknam T, Fard ET, Pourjafarian N, Rousta A (2011) An efficient hybrid algorithm based on modified imperialist competitive algorithm and K-means for data clustering. Eng Appl Artif Intell 24(2):306–317
68. Khabbazi A, Atashpaz-Gargari E, Lucas C (2009) Imperialist competitive algorithm for minimum bit error rate beamforming. Int J Bio-Inspired Comput 1(1–2):125–133
69. Hosseini S, Al Khaled A (2014) A survey on the imperialist competitive algorithm metaheuristic: implementation in engineering domain and directions for future research. Appl Soft Comput 24:1078–1094
70. Ahmadi MA, Ebadi M, Shokrollahi A, Majidi SMJ (2013) Evolving artificial neural network and imperialist competitive algorithm for prediction oil flow rate of the reservoir. Appl Soft Comput 13(2):1085–1098
71. Nazari-Shirkouhi S, Eivazy H, Ghodsi R, Rezaie K, Atashpaz-Gargari E (2010) Solving the integrated product mix-outsourcing problem using the imperialist competitive algorithm. Expert Syst Appl 37(12):7615–7626
72. Coelho LDS, Afonso LD, Alotto P (2012) A modified imperialist competitive algorithm for optimization in electromagnetics. IEEE Trans Magn 48(2):579–582
73. Taher SA, Fini MH, Aliabadi SF (2014) Fractional order PID controller design for LFC in electric power systems using imperialist competitive algorithm. Ain Shams Eng J 5(1):121–135
74. Abd-Elazim SM, Ali ES (2016) Imperialist competitive algorithm for optimal STATCOM design in a multimachine power system. Int J Electr Power Energy Syst 76:136–146
75. Razmjooy N, Mousavi BS, Soleymani F (2013) A hybrid neural network imperialist competitive algorithm for skin color segmentation. Math Comput Model 57(3–4):848–856
76. Razmjooy N, Mousavi BS, Sadeghi B, Khalilpour M (2011, July). Image thresholding optimization based on imperialist competitive algorithm. In 3rd Iranian conference on electrical and electronics engineering (ICEEE2011) (pp. 1–10). Iran: Islamic Azad University of Gonabad.
77. Hajihassani M, Armaghani DJ, Marto A, Mohamad ET (2015) Ground vibration prediction in quarry blasting through an artificial neural network optimized by imperialist competitive algorithm. Bull Eng Geol Env 74(3):873–886
78. Jasour AM, Atashpaz E, Lucas C (2008) Vehicle fuzzy controller design using imperialist competitive algorithm. In Second first Iranian joint congress on fuzzy and intelligent systems, Tehran, Iran (pp. 1–6).
79. Ghasemi M, Ghavidel S, Ghanbarian MM, Massrur HR, Gharibzadeh M (2014) Application of imperialist competitive algorithm with its modified techniques for multi-objective optimal power flow problem: a comparative study. Inf Sci 281:225–247
80. Shokrollahpour E, Zandieh M, Dorri B (2011) A novel imperialist competitive algorithm for bi-criteria scheduling of the assembly flowshop problem. Int J Prod Res 49(11):3087–3103
81. Enayatifar R, Abdullah AH, Lee M (2013) A weighted discrete imperialist competitive algorithm (WDICA) combined with chaotic map for image encryption. Opt Lasers Eng 51(9):1066–1077
82. Kashan AH (2009, December). League championship algorithm: a new algorithm for numerical function optimization. In 2009 international conference of soft computing and pattern recognition (pp. 43–48). IEEE.
83. Kashan AH (2014) League Championship Algorithm (LCA): an algorithm for global optimization inspired by sport championships. Appl Soft Comput 16:171–200
84. Bouchekara HREH, Abido MA, Chaib AE, Mehasni R (2014) Optimal power flow using the league championship algorithm: a case study of the Algerian power system. Energy Convers Manage 87:58–70

85. Abdulhamid SM, Latiff MSA, Idris I (2015). Tasks scheduling technique using league championship algorithm for makespan minimization in IAAS cloud. arXiv preprint arXiv:1510.03173.
86. Wangchamhan T, Chiewchanwattana S, Sunat K (2017) Efficient algorithms based on the k-means and Chaotic League Championship Algorithm for numeric, categorical, and mixed-type data clustering. Expert Syst Appl 90:146–167
87. Alimoradi MR, Kashan AH (2018) A league championship algorithm equipped with network structure and backward Q-learning for extracting stock trading rules. Appl Soft Comput 68:478–493
88. Eita MA, Fahmy MM (2010) Group counseling optimization: a novel approach. In Research and development in intelligent systems XXVI (pp. 195–208). Springer: London.
89. Eita MA, Fahmy MM (2014) Group counseling optimization. Appl Soft Comput 22:585–604
90. Ali H, Khan FA (2013, June). Group counseling optimization for multi-objective functions. In 2013 IEEE congress on evolutionary computation (pp. 705–712). IEEE.
91. Lv W, He C, Li D, Cheng S, Luo S, Zhang X (2010) Election campaign optimization algorithm. Procedia Comput Sci 1(1):1377–1386
92. Zhang H, Lv WG, Cheng SY, Luo SM, Zhang XW (2011) Election campaign optimization algorithm for design of pressure vessel. Adv Mater Res 308:15–20
93. Abubakar H, Sathasivam S (2020) Comparing election algorithm and election campaign optimization algorithm. AIP Conf Proc 2266(1):040006
94. Xu Y, Cui Z, Zeng J (2010) Social emotional optimization algorithm for nonlinear constrained optimization problems. In: Panigrahi BK (ed) International conference on swarm, evolutionary, and memetic computing. Springer, Berlin, Heidelberg, pp 583–590
95. Cui Z, Shi Z, Zeng J (2010) Using social emotional optimization algorithm to direct orbits of chaotic systems. In: Panigrahi BK (ed) International conference on swarm, evolutionary, and memetic computing. Springer, Berlin, Heidelberg, pp 389–395
96. Rao RV, Savsani VJ, Vakharia DP (2011) Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems. Comput Aided Des 43(3):303–315
97. Toğan V (2012) Design of planar steel frames using teaching–learning based optimization. Eng Struct 34:225–232
98. Rao RV, Savsani VJ, Vakharia DP (2012) Teaching–learning-based optimization: an optimization method for continuous non-linear large scale problems. Inf Sci 183(1):1–15
99. Rao RV, Patel V (2013) Multi-objective optimization of heat exchangers using a modified teaching-learning-based optimization algorithm. Appl Math Model 37(3):1147–1162
100. Yu K, Wang X, Wang Z (2016) An improved teaching-learning-based optimization algorithm for numerical and engineering optimization problems. J Intell Manuf 27(4):831–843
101. Zhang Y, Jin Z, Chen Y (2020) Hybrid teaching–learning-based optimization and neural network algorithm for engineering design optimization problems. Knowl-Based Syst 187:104836
102. Rao RV, More KC (2015) Optimal design of the heat pipe using TLBO (teaching–learning-based optimization) algorithm. Energy 80:535–544
103. Degertekin SO, Hayalioglu MS (2013) Sizing truss structures using teaching-learning-based optimization. Comput Struct 119:177–188
104. Rao RV, Patel V (2013) Multi-objective optimization of two stage thermoelectric cooler using a modified teaching–learning-based optimization algorithm. Eng Appl Artif Intell 26(1):430–445
105. Chatterjee S, Mukherjee V (2016) PID controller for automatic voltage regulator using teaching–learning based optimization technique. Int J Electr Power Energy Syst 77:418–429
106. Ji X, Ye H, Zhou J, Yin Y, Shen X (2017) An improved teaching-learning-based optimization algorithm and its application to a combinatorial optimization problem in foundry industry. Appl Soft Comput 57:504–516
107. Sultana S, Roy PK (2014) Optimal capacitor placement in radial distribution systems using teaching learning based optimization. Int J Electr Power Energy Syst 54:387–398
108. Anbazhagan S (2021) Application of teaching learning based optimization in multilevel image thresholding. ICTACT J Image Video Process 11(4):2413–2422
109. Shi Y (2011) Brain storm optimization algorithm. In: Tan Y et al (eds) International conference in swarm intelligence. Springer, Berlin, Heidelberg, pp 303–309
110. Pourpanah F, Shi Y, Lim CP, Hao Q, Tan CJ (2019) Feature selection based on brain storm optimization for data classification. Appl Soft Comput 80:761–775
111. Narmatha C, Eljack SM, Tuka AARM, Manimurugan S, Mustafa M (2020) A hybrid fuzzy brain-storm optimization algorithm for the classification of brain tumor MRI images. J Ambient Intell Humanized Comput. https://doi.org/10.1007/s12652-020-02470-5
112. Papa JP, Rosa GH, de Souza AN, Afonso LC (2018) Feature selection through binary brain storm optimization. Comput Electr Eng 72:468–481
113. Zhang WQ, Zhang Y, Peng C (2019) Brain storm optimization for feature selection using new individual clustering and updating mechanism. Appl Intell 49(12):4294–4302
114. Tuba E, Jovanovic R, Zivkovic D, Beko M, Tuba M (2019) Clustering algorithm optimized by brain storm optimization for digital image segmentation. In 2019 7th international symposium on digital forensics and security (ISDFS) (pp. 1–6). IEEE.
115. Xue J, Wu Y, Shi Y, Cheng S (2012, June) Brain storm optimization algorithm for multi-objective optimization problems. In International conference in swarm intelligence (pp. 513–519). Springer: Berlin, Heidelberg.
116. Cheng S, Shi Y, Qin Q, Gao S (2013, April) Solution clustering analysis in brain storm optimization algorithm. In 2013 IEEE symposium on swarm intelligence (SIS) (pp. 111–118). IEEE.
117. Xue X, Lu J (2020) A compact brain storm algorithm for matching ontologies. IEEE Access 8:43898–43907
118. Li J, Duan H (2015) Simplified brain storm optimization approach to control parameter optimization in F/A-18 automatic carrier landing system. Aerosp Sci Technol 42:187–195
119. Ahmadi-Javid A (2011, June) Anarchic society optimization: a human-inspired method. In 2011 IEEE congress of evolutionary computation (CEC) (pp. 2586–2592). IEEE.
120. Shayeghi H, Dadashpour J (2012) Anarchic society optimization based PID control of an automatic voltage regulator (AVR) system. Electric Electron Eng 2(4):199–207
121. Ahmadi-Javid A, Hooshangi-Tabrizi P (2012, July) An anarchic society optimization algorithm for a flow-shop scheduling problem with multiple transporters between successive machines. In International conference on industrial engineering and operations management (ICIEOM), Istanbul, Turkey (pp. 3–6).
122. Bozorgi A, Bozorg-Haddad O, Rajabi MM, Latifi M, Chu X (2017) Applications of the anarchic society optimization (ASO) algorithm for optimizing operations of single and continuous multi-reservoir systems. J Water Supply: Res Technol 66(7):556–573
123. Bozorg-Haddad O, Latifi M, Bozorgi A, Rajabi MM, Naeeni ST, Loáiciga HA (2018) Development and application of the

anarchic society algorithm (ASO) to the optimal operation of water distribution networks. Water Sci Technol 18(1):318–332
124. Kulkarni AJ, Durugkar IP, Kumar M (2013, October) Cohort intelligence: a self supervised learning behavior. In 2013 IEEE international conference on systems, man, and cybernetics (pp. 1396–1400). IEEE.
125. Krishnasamy G, Kulkarni AJ, Paramesran R (2014) A hybrid approach for data clustering based on modified cohort intelligence and K-means. Expert Syst Appl 41(13):6009–6016
126. Kulkarni AJ, Baki MF, Chaouch BA (2016) Application of the cohort-intelligence optimization method to three selected combinatorial optimization problems. Eur J Oper Res 250(2):427–447
127. Kulkarni O, Kulkarni N, Kulkarni AJ, Kakandikar G (2018) Constrained cohort intelligence using static and dynamic penalty function approach for mechanical components design. Int J Parallel Emergent Distrib Syst 33(6):570–588
128. Shastri AS, Nargundkar A, Kulkarni AJ, Sharma KK (2020) Multi-cohort intelligence algorithm for solving advanced manufacturing process problems. Neural Comput Appl 32(18):15055–15075
129. Kuo HC, Lin CH (2013) Cultural evolution algorithm for global optimizations and its applications. J Appl Res Technol 11(4):510–522
130. Civicioglu P (2013) Backtracking search optimization algorithm for numerical optimization problems. Appl Math Comput 219(15):8121–8144
131. El-Fergany A (2015) Optimal allocation of multi-type distributed generators using backtracking search optimization algorithm. Int J Electr Power Energy Syst 64:1197–1205
132. Chaib AE, Bouchekara HREH, Mehasni R, Abido MA (2016) Optimal power flow with emission and non-smooth cost functions using backtracking search optimization algorithm. Int J Electr Power Energy Syst 81:64–77
133. Guney K, Durmus A, Basbug S (2014) Backtracking search optimization algorithm for synthesis of concentric circular antenna arrays. Int J Antennas Propagation, 2014.
134. Chen L, Sun N, Zhou C, Zhou J, Zhou Y, Zhang J, Zhou Q (2018) Flood forecasting based on an improved extreme learning machine model combined with the backtracking search optimization algorithm. Water 10(10):1362
135. Gandomi AH (2014) Interior search algorithm (ISA): a novel approach for global optimization. ISA Trans 53(4):1168–1183
136. Rizk-Allah RM, Hassanien AE (2022) COVID-19 Forecasting Based on an Improved Interior Search Algorithm and Multilayer Feed-Forward Neural Network. In Medical informatics and bioimaging using artificial intelligence (pp. 129–152). Springer: Cham.
137. Talatahari S, Azizi M (2020) Optimum design of building structures using tribe-interior search algorithm. Structures 28:1616–1633
138. Gandomi AH, Roke DA (2014, December). Engineering optimization using interior search algorithm. In 2014 IEEE symposium on swarm intelligence (pp. 1–7). IEEE.
139. Arora S, Sharma M, Anand P (2020) A novel chaotic interior search algorithm for global optimization and feature selection. Appl Artif Intell 34(4):292–328
140. Moosavian N, Roodsari BK (2014) Soccer league competition algorithm: a novel meta-heuristic algorithm for optimal design of water distribution networks. Swarm Evol Comput 17:14–24
141. Moosavian N (2015) Soccer league competition algorithm for solving knapsack problems. Swarm Evol Comput 20:14–22
142. Moosavian N, Roodsari BK (2013) Soccer league competition algorithm, a new method for solving systems of nonlinear equations. Int J Intell Sci 4(01):7
143. Ebrahimi S, Tabatabaei S (2020) Using clustering via soccer league competition algorithm for optimizing power consumption in wsns (wireless sensor networks). Wireless Pers Commun 113(4):2387–2402
144. Moosavian N, Moosavian H (2017) Testing soccer league competition algorithm in comparison with ten popular metaheuristic algorithms for sizing optimization of truss structures. Int J Eng 30(7):926–936
145. Ghorbani N, Babaei E (2014) Exchange market algorithm. Appl Soft Comput 19:177–187
146. Ghorbani N, Babaei E (2016) Exchange market algorithm for economic load dispatch. Int J Electr Power Energy Syst 75:19–27
147. Rajan A, Malakar T (2016) Optimum economic and emission dispatch using exchange market algorithm. Int J Electr Power Energy Syst 82:545–560
148. Sathya PD, Kalyani R, Sakthivel VP (2021) Color image segmentation using kapur, otsu and minimum cross entropy functions based on exchange market algorithm. Expert Syst Appl 172:114636
149. Emami H, Derakhshan F (2015) Election algorithm: A new socio-politically inspired strategy. AI Commun 28(3):591–603
150. Luo Y, Chen Y, Chen Q, Liang Q (2018, November) A new election algorithm for DPos consensus mechanism in blockchain. In 2018 7th international conference on digital home (ICDH) (pp. 116–120). IEEE.
151. Sathasivam S, Mansor M, Kasihmuddin MSM, Abubakar H (2020) Election algorithm for random k satisfiability in the Hopfield neural network. Processes 8(5):568
152. Saidi A, Benahmed K, Seddiki N (2020) Secure cluster head election algorithm and misbehavior detection approach based on trust management technique for clustered wireless sensor networks. Ad Hoc Netw 106:102215
153. Savsani P, Savsani V (2016) Passing vehicle search (PVS): A novel metaheuristic algorithm. Appl Math Model 40(5–6):3951–3978
154. Kumar S, Tejani GG, Pholdee N, Bureerat S (2021) Multiobjective passing vehicle search algorithm for structure optimization. Expert Syst Appl 169:114511
155. Ram Prabhu T, Savsani V, Parsana S, Radadia N, Sheth M, Sheth N (2018) Multi-objective optimization of EDM process parameters by using Passing Vehicle Search (PVS) algorithm. Defect Diffusion Forum 382:138–146
156. Ladumor DP, Trivedi IN, Bhesdadiya RH, Jangir P (2017, February) A passing vehicle search algorithm for solution of optimal power flow problems. In 2017 third international conference on advances in electrical, electronics, information, communication and bio-informatics (AEEICB) (pp. 268–273). IEEE.
157. Chentoufi MA, Ellaia R (2021) A novel multiobjective passing vehicle search algorithm for signal timing optimization. Comput Sci 16(2):775–792
158. Rao R (2016) Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems. Int J Ind Eng Comput 7(1):19–34
159. Rao RV, Saroj A (2017) A self-adaptive multi-population based Jaya algorithm for engineering optimization. Swarm Evol Comput 37:1–26
160. Yu K, Qu B, Yue C, Ge S, Chen X, Liang J (2019) A performance-guided JAYA algorithm for parameters identification of photovoltaic cell and module. Appl Energy 237:241–257
161. Rao RV, Rai DP, Balic J (2016) Surface grinding process optimization using Jaya algorithm. Comput Intell Data Mining 2:487–495
162. Satapathy SC, Rajinikanth V (2018) Jaya algorithm guided procedure to segment tumor from brain MRI. J Optim 2018.

163. Kaveh A, Zolghadr A (2016) A novel meta-heuristic algorithm: tug of war optimization. Iran Univ Sci Technol 6(4):469–492
164. Kaveh A, Zolghadr A (2017) Guided modal strain energy-based approach for structural damage identification using tug-of-war optimization algorithm. J Comput Civ Eng 31(4):04017016
165. Nguyen T, Hoang B, Nguyen G, Nguyen BM (2020) A new workload prediction model using extreme learning machine and enhanced tug of war optimization. Procedia Comput Sci 170:362–369
166. Kaveh A, Shokohi F (2016) Optimum design of laterally-supported castellated beams using tug of war optimization algorithm. Struct Eng Mech 3(58):533–553
167. Kaveh A, Shokohi F, Ahmadi B (2017) Optimal analysis and design of water distribution systems using tug of war optimization algorithm. دانشگاه علم و صنعت ایران 7(2):193–210
168. Satapathy S, Naik A (2016) Social group optimization (SGO): a new population evolutionary optimization technique. Complex Intell Syst 2(3):173–203
169. Naik A, Satapathy SC, Ashour AS, Dey N (2018) Social group optimization for global optimization of multimodal functions and data clustering problems. Neural Comput Appl 30(1):271–287
170. Dey N, Rajinikanth V, Ashour AS, Tavares JMR (2018) Social group optimization supported segmentation and evaluation of skin melanoma images. Symmetry 10(2):51
171. Praveen SP, Rao KT, Janakiramaiah B (2018) Effective allocation of resources and task scheduling in cloud environment using social group optimization. Arab J Sci Eng 43(8):4265–4272
172. Singh AK, Kumar A, Mahmud M, Kaiser MS, Kishore A (2021) COVID-19 infection detection from chest X-ray images using hybrid social group optimization and support vector classifier. Cogn Comput 1–13.
173. Liu ZZ, Chu DH, Song C, Xue X, Lu BY (2016) Social learning optimization (SLO) algorithm paradigm and its application in QoS-aware cloud service composition. Inf Sci 326:315–333
174. Liu Z, Qin J, Peng W, Chao H (2017) Effective task scheduling in cloud computing based on improved social learning optimization algorithm. Int J Online Eng 13(6):4
175. Fadakar E, Ebrahimi M (2016, March) A new metaheuristic football game inspired algorithm. In 2016 1st conference on swarm intelligence and evolutionary computation (CSIEC) (pp. 6–11). IEEE.
176. Djunaidi AV, Juwono CP (2018) Football game algorithm implementation on the capacitated vehicle routing problems. Int J Comput Algoritm 7(1):45–53
177. Huan TT, Kulkarni AJ, Kanesan J, Huang CJ, Abraham A (2017) Ideology algorithm: a socio-inspired optimization methodology. Neural Comput Appl 28(1):845–876
178. Bouchekara HREH (2020) Most valuable player algorithm: a novel optimization algorithm inspired from sport. Oper Res Int Journal 20(1):139–195
179. Pervez I, Shams I, Mekhilef S, Sarwar A, Tariq M, Alamri B (2021) Most valuable player algorithm based maximum power point tracking for a partially shaded PV generation system. IEEE Trans Sustain Energy 12(4):1876–1890
180. Ramli MA, Bouchekara HR (2020) Wind farm layout optimization considering obstacles using a binary most valuable player algorithm. IEEE Access 8:131553–131564
181. Korashy A, Kamel S, Youssef AR, Jurado F (2019, February) Most valuable player algorithm for solving direction overcurrent relays coordination problem. In 2019 International conference on innovative trends in computer engineering (ITCE) (pp. 466–471). IEEE.
182. Ahmadi SA (2017) Human behavior-based optimization: a novel metaheuristic approach to solve complex optimization problems. Neural Comput Appl 28(1):233–244
183. Soto R, Crawford B, González F, Vega E, Castro C, Paredes F (2019) Solving the manufacturing cell design problem using human behavior-based algorithm supported by autonomous search. IEEE Access 7:132228–132239
184. Soto R, Crawford B, González F, Olivares R (2021) Human behaviour based optimization supported with self-organizing maps for solving the S-box design Problem. IEEE Access 9:84605–84618
185. Behkam, R., Vahidi, B., Zolfaghari, M., Naderi, M. S., & Gharehpetian, G. B. (2020, August). HBBO-based intelligent setting and coordination of directional overcurrent relays considering different characteristics. In 2020 28th Iran conference on electrical engineering (ICEE) (pp. 1–4). IEEE.
186. Mousavirad SJ, Ebrahimpour-Komleh H (2017) Human mental search: a new population-based metaheuristic optimization algorithm. Appl Intell 47(3):850–887
187. Mousavirad SJ, Ebrahimpour-Komleh H, Schaefer G (2019) Effective image clustering based on human mental search. Appl Soft Comput 78:209–220
188. Mousavirad SJ, Ebrahimpour-Komleh H, Schaefer G (2020) Automatic clustering using a local search-based human mental search algorithm for image segmentation. Appl Soft Comput 96:106604
189. Esmaeili L, Mousavirad SJ, Shahidinejad A (2021) An efficient method to minimize cross-entropy for selecting multi-level threshold values using an improved human mental search algorithm. Expert Syst Appl 182:115106
190. Mousavirad SJ, Ebrahimpour-Komleh H (2020) Human mental search-based multilevel thresholding for image segmentation. Appl Soft Comput 97:105427
191. Mousavirad SJ, Schaefer G, Esmaeili L, Korovin I (2020, July) On improvements of the human mental search algorithm for global optimisation. In 2020 IEEE congress on evolutionary computation (CEC) (pp. 1–8). IEEE.
192. Mousavirad SJ, Schaefer G, Celebi ME, Fang H, Liu X (2020, October) Colour quantisation using human mental search and local refinement. In 2020 IEEE international conference on systems, man, and cybernetics (SMC) (pp. 3045–3050). IEEE.
193. Fathollahi-Fard AM, Hajiaghaei-Keshteli M, Tavakkoli-Moghaddam R (2018) The social engineering optimizer (SEO). Eng Appl Artif Intell 72:267–293
194. Fathollahi-Fard AM, Ranjbar-Bourani M, Cheikhrouhou N, Hajiaghaei-Keshteli M (2019) Novel modifications of social engineering optimizer to solve a truck scheduling problem in a cross-docking system. Comput Ind Eng 137:106103
195. Zhang C, Fathollahi-Fard AM, Li J, Tian G, Zhang T (2021) Disassembly sequence planning for intelligent manufacturing using social engineering optimizer. Symmetry 13(4):663
196. Baliarsingh SK, Ding W, Vipsita S, Bakshi S (2019) A memetic algorithm using emperor penguin and social engineering optimization for medical data classification. Appl Soft Comput 85:105773
197. Aghamohamadi S, Rabbani M, Tavakkoli-Moghaddam R (2021) A social engineering optimizer algorithm for a closed-loop supply chain system with uncertain demand. Int J Transport Eng 9(1):521–536
198. Millán-Páramo, C., Millán-Romero, E., & Wilches, F. J. Truss optimization with natural frequency constraints using modified social engineering optimizer.
199. Mamedova N, Urintsov A, Staroverova O, Ivanov E, Galahov D (2019) Social engineering in the context of ensuring information security. SHS Web of Conferences 69:00073

200. Zhang J, Xiao M, Gao L, Pan Q (2018) Queuing search algorithm: a novel metaheuristic algorithm for solving engineering optimization problems. Appl Math Model 63:464–490
201. Thaher T, Mafarja M, Abdalhaq B, Chantar H (2019, October) Wrapper-based feature selection for imbalanced data using binary queuing search algorithm. In 2019 2nd international conference on new trends in computing sciences (ICTCS) (pp. 1–6). IEEE.
202. Zheng X, Nguyen H (2022) A novel artificial intelligent model for predicting water treatment efficiency of various biochar systems based on artificial neural network and queuing search algorithm. Chemosphere 287:132251
203. Mahmoodabadi MJ, Rasekh M, Zohari T (2018) TGA: team game algorithm. Future Comput Inform J 3(2):191–199
204. He Y, Hao X, Li W, Zhai Q (2021) Binary team game algorithm based on modulo operation for knapsack problem with a single continuous variable. Appl Soft Comput 103:107180
205. Mahmoodabadi MJ (2021) Moving least squares approximation-based online control optimised by the team game algorithm for Duffing-Holmes chaotic problems. Cyber-Physical Systems 7(2):93–113
206. Kumar M, Kulkarni AJ, Satapathy SC (2018) Socio evolution & learning optimization algorithm: a socio-inspired optimization methodology. Futur Gener Comput Syst 81:252–272
207. Moghdani R, Salimifard K (2018) Volleyball premier league algorithm. Appl Soft Comput 64:161–185
208. Abd Elaziz M, Nabil N, Moghdani R, Ewees AA, Cuevas E, Lu S (2021) Multilevel thresholding image segmentation based on improved volleyball premier league algorithm using whale optimization algorithm. Multimedia Tools App 80(8):12435–12468
209. Das P, Das DK, Dey S (2018) A new class topper optimization algorithm with an application to data clustering. IEEE Trans Emerg Top Comput 8(4):948–959
210. Srivastava A, Das DK (2020) A new aggrandized class topper optimization algorithm to solve economic load dispatch problem in a power system. IEEE Trans Cybern.
211. Rai A, Das DK (2020) Optimal pid controller design by enhanced class topper optimization algorithm for load frequency control of interconnected power systems. Smart Sci 8(3):125–151
212. Mohanta TK, Das DK (2021) Class topper optimization based improved localization algorithm in wireless sensor network. Wireless Pers Commun 119(4):3319–3338
213. Fattahi E, Bidar M, Kanan HR (2018) Focus group: an optimization algorithm inspired by human behavior. Int J Comput Intell Appl 17(01):1850002
214. Singh PR, Abd Elaziz M, Xiong S (2019) Ludo game-based metaheuristics for global and engineering optimization. Appl Soft Comput 84:105723
215. Irene DS, Beulah JR (2022) An efficient COVID-19 detection from CT images using ensemble support vector machine with Ludo game-based swarm optimisation. Comput Methods Biomec Biomed Eng: Imaging Visual, 1–12.
216. Shabani A, Asgarian B, Gharebaghi SA, Salido MA, Giret A (2019) A new optimization algorithm based on search and rescue operations. Math Prob Eng 2019:1–23
217. Shabani A, Asgarian B, Salido M, Gharebaghi SA (2020) Search and rescue optimization algorithm: a new optimization method for solving constrained engineering optimization problems. Expert Syst Appl 161:113698
218. Khatri A, Gaba A, Rana KPS, Kumar V (2020) A novel life choice-based optimizer. Soft Comput 24(12):9121–9141
219. Tharwat A, Gabel T (2019) Parameters optimization of support vector machines for imbalanced data using social ski driver algorithm. In Neural computing and applications, pp. 1–14.
220. Chatterjee B, Bhattacharyya T, Ghosh KK, Singh PK, Geem ZW, Sarkar R (2020) Late acceptance hill climbing based social ski driver algorithm for feature selection. IEEE Access 8:75393–75408
221. Mohamed AW, Hadi AA, Mohamed AK (2019) Gaining-sharing knowledge based algorithm for solving optimization problems: a novel nature-inspired algorithm. Int J Mach Learn Cybern, 1–29.
222. Mohamed AW, Abutarboush HF, Hadi AA, Mohamed AK (2021) Gaining-sharing knowledge based algorithm with adaptive parameters for engineering optimization. IEEE Access 9:65934–65946
223. Pare S, Bhandari AK, Kumar A, Bajaj V (2018) Backtracking search algorithm for color image multilevel thresholding. SIViP 12(2):385–392
224. Ortega-Sánchez N, Rodríguez-Esparza E, Oliva D, Pérez-Cisneros M, Mohamed AW, Dhiman G, Hernández-Montelongo R (2021) Identification of apple diseases in digital images by using the Gaining-sharing knowledge-based algorithm for multilevel thresholding. Soft Comput, 1–37.
225. Agrawal P, Ganesh T, Mohamed AW (2021) A novel binary gaining–sharing knowledge-based optimization algorithm for feature selection. Neural Comput Appl 33(11):5989–6008
226. Agrawal, P., Ganesh, T., & Mohamed, A. W. (2021). Solving knapsack problems using a binary gaining sharing knowledge-based optimization algorithm. Complex & Intelligent Systems, 1–21.
227. Xiong G, Li L, Mohamed AW, Yuan X, Zhang J (2021) A new method for parameter extraction of solar photovoltaic models using gaining–sharing knowledge based algorithm. Energy Rep 7:3286–3301
228. Xiong G, Yuan X, Mohamed AW, Zhang J (2022) Fault section diagnosis of power systems with logical operation binary gaining-sharing knowledge-based algorithm. Int J Intell Syst 37:1057–1080
229. Agrawal P, Ganesh T, Mohamed AW (2020, July) Solution of uncertain solid transportation problem by integer gaining sharing knowledge based optimization algorithm. In 2020 international conference on computational performance evaluation (ComPE) (pp. 158–162). IEEE.
230. Elsisi M (2019) Future search algorithm for optimization. Evol Intel 12(1):21–31
231. Janamala V, Kumar UK, Pandraju TKS (2021) Future search algorithm for optimal integration of distributed generation and electric vehicle fleets in radial distribution networks considering techno-environmental aspects. SN Appl Sci 3(4):1–17
232. Elsisi M, Soliman M (2021) Optimal design of robust resilient automatic voltage regulators. ISA Trans 108:257–268
233. Shaheen AM, Ginidi AR, El-Sehiemy RA, Ghoneim SS (2020) A forensic-based investigation algorithm for parameter extraction of solar cell models. IEEE Access 9:1–20
234. Hoang ND, Huynh TC, Tran VD (2021) Computer vision-based patched and unpatched pothole classification using machine learning approach optimized by forensic-based investigation metaheuristic. Complexity 2021:1–17
235. Chou JS, Truong DN (2022) Multiobjective forensic-based investigation algorithm for solving structural design problems. Autom Constr 134:104084
236. Kuyu YÇ, Vatansever F (2021) Modified forensic-based investigation algorithm for global optimization. Eng Comput. https://doi.org/10.1007/s00366-021-01322-w
237. Askari Q, Younas I, Saeed M (2020) Political optimizer: a novel socio-inspired meta-heuristic for global optimization. Knowl-Based Syst 195:105709
238. Awad R (2021) October). Sizing optimization of truss structures using the political optimizer (PO) algorithm. Structures 33:4871–4894

239. Diab AAZ, Tolba MA, El-Magd AGA, Zaky MM, El-Rifaie AM (2020) Fuel cell parameters estimation via marine predators and political optimizers. IEEE Access 8:166998–167018
240. Manita Ghaith, Korbaa Ouajdi (2020) Binary political optimizer for feature selection using gene expression data. Comput Intell Neurosci 2020:1–14
241. Premkumar M, Sowmya R, Jangir P, Kumar JS (2020, October) A new and reliable objective functions for extracting the unknown parameters of solar photovoltaic cell using political optimizer algorithm. In 2020 international conference on data analytics for business and industry: way towards a sustainable economy (ICDABI) (pp. 1–6). IEEE.
242. Durmus A, Kurban R (2021). Optimal synthesis of concentric circular antenna arrays using political optimizer. IETE J Res, 1–10.
243. Singh P, Pandit M, Srivastava L (2020, September) Optimization of levelized cost of hybrid wind-solar-diesel-battery system using political optimizer. In 2020 IEEE first international conference on smart technologies for power, energy and control (STPEC) (pp. 1–6). IEEE.
244. Mani V, Varma MD, Krishna KV, Khan Z, Sudabattula SK. Hybrid approach to solve capacitor allocation problem in distribution system using political optimizer algorithm.
245. Basetti V, Rangarajan SS, Shiva CK, Pulluri H, Kumar R, Collins RE, Senjyu T (2021) Economic emission load dispatch problem with valve-point loading using a novel quasi-oppositional-based political optimizer. Electronics 10(21):2596
246. Askari Q, Saeed M, Younas I (2020) Heap-based optimizer inspired by corporate rank hierarchy for global optimization. Expert Syst Appl 161:113702
247. Rizk-Allah RM, El-Fergany AA (2021) Emended heap-based optimizer for characterizing performance of industrial solar generating units using triple-diode model. Energy 237:121561
248. Abdel-Basset M, Mohamed R, Elhoseny M, Chakrabortty RK, Ryan MJ (2021) An efficient heap-based optimization algorithm for parameters identification of proton exchange membrane fuel cells model: analysis and case studies. Int J Hydrogen Energy 46(21):11908–11925
249. Shaheen AM, Elsayed AM, Ginidi AR, El-Sehiemy RA, Elattar EE (2022) Improved heap-based optimizer for dg allocation in reconfigured radial feeder distribution systems. IEEE Syst J. https://doi.org/10.1109/JSYST.2021.3136778
250. Elsayed SK, Kamel S, Selim A, Ahmed M (2021) An improved heap-based optimizer for optimal reactive power dispatch. IEEE Access 9:58319–58336
251. Shaheen MA, Hasanien HM, Al-Durra A (2021) Solving of optimal power flow problem including renewable energy resources using HEAP optimization algorithm. IEEE Access 9:35846–35863
252. Kharrich M, Kamel S, Hassan MH, ElSayed SK, Taha I (2021) An improved heap-based optimizer for optimal design of a hybrid microgrid considering reliability and availability constraints. Sustainability 13(18):10419
253. Wadhwa H, Aron R (2022) A clustering-based optimization of resource utilization in fog computing. In JK Mandal, R Buyya, D De (Eds.), *Proceedings of International Conference on Advanced Computing Applications* (pp. 343–353). Springer, Singapore.
254. Ghasemian H, Ghasemian F, Vahdat-Nejad H (2020) Human urbanization algorithm: a novel metaheuristic approach. Math Comput Simul 178:1–15
255. Alluri A, Lanka RS, Rao RS (2021) System security enhancement using hybrid HUA-GPC approach under transmission line (s) and/or generator (s) outage conditions. Int J Numerical Model: Electron Netw, Devices Fields.
256. Rahkar Farshi T (2021) Battle royale optimization algorithm. Neural Comput Appl 33:1139–1157
257. Agahian S, Akan T (2021) Battle royale optimizer for training multi-layer perceptron. Evol Syst. https://doi.org/10.1007/s12530-021-09401-5
258. Şahin AK, Taş T, Bertuğ E, Ayas MŞ (2021, June) Metaheuristic algorithm based PI controller design for Linearized Quadruple-Tank Process. In 2021 3rd international congress on human-computer interaction, optimization and robotic applications (HORA) (pp. 1–6). IEEE.
259. Suresh G, Prasad D, Gopila M (2021) An efficient approach based power flow management in smart grid system with hybrid renewable energy sources. Renew Energy Focus 39:110–122
260. Wagan AI, Shaikh MM (2020) A new metaheuristic optimization algorithm inspired by human dynasties with an application to the wind turbine micrositing problem. Appl Soft Comput 90:106176
261. Al-Betar MA, Alyasseri ZAA, Awadallah MA, Doush IA (2021) Coronavirus herd immunity optimizer (CHIO). Neural Comput Appl 33(10):5011–5042
262. Dalbah LM, Al-Betar MA, Awadallah MA, Zitar RA (2021) A modified coronavirus herd immunity optimizer for capacitated vehicle routing problem. J King Saud University-Comput Inform Sci.
263. Dalbah LM, Al-Betar MA, Awadallah MA, Zitar RA (2022). A coronavirus herd immunity optimization (chio) for travelling salesman problem. In International conference on innovative computing and communications (pp. 717–729). Springer, Singapore.
264. Alweshah M, Alkhalaileh S, Al-Betar MA, Bakar AA (2022) Coronavirus herd immunity optimizer with greedy crossover for feature selection in medical diagnosis. Knowl-Based Syst 235:107629
265. Kumar C, Magdalin Mary D, Gunasekar T (2022) MOCHIO: a novel multi-objective coronavirus herd immunity optimization algorithm for solving brushless direct current wheel motor design optimization problem. Automatika 63(1):149–170
266. Naderipour A, Abdullah A, Marzbali MH, Nowdeh SA (2022) An improved corona-virus herd immunity optimizer algorithm for network reconfiguration based on fuzzy multi-criteria approach. Expert Syst Appl 187:115914
267. Amini S, Ghasemi S, Golpira H, Anvari-Moghaddam A (2021, September). Coronavirus herd immunity optimizer (CHIO) for Transmission Expansion Planning. In 2021 IEEE international conference on environment and electrical engineering and 2021 IEEE industrial and commercial power systems Europe (EEEIC/I&CPS Europe) (pp. 1–6). IEEE.
268. Alqarni, M. Sodium sulfur batteries allocation in high renewable penetration microgrids using coronavirus herd immunity optimization. Ain Shams Eng J (2021).
269. Mahboob AS, Shahhoseini HS, Moghaddam MRO, Yousefi S (2021, May) A coronavirus herd immunity optimizer for intrusion detection system. In 2021 29th Iranian conference on electrical engineering (ICEE) (pp. 579–585). IEEE.
270. Zitar R (2021) A modified coronavirus herd immunity optimizer for capacitated vehicle routing problem.
271. Emami H (2022) Stock exchange trading optimization algorithm: a human-inspired method for global optimization. J Supercomput 78(2):2125–2174
272. Emami H (2022) Anti-coronavirus optimization algorithm. Soft Comput 26(11):4991–5023
273. Kalyani R, Sathya PD, Sakthivel VP (2021) Medical image segmentation using exchange market algorithm. Alex Eng J 60(6):5039–5063
274. Sovatzidi G, Savelonas M, Koutsiou DCC, Iakovidis DK (2020, October). Image segmentation based on determinative brain storm optimization. In 2020 15th international workshop on

semantic and social media adaptation and personalization (SMA) (pp. 1–6). IEEE.
275. Dey N, Rajinikanth V, Shi F, Tavares JMR, Moraru L, Karthik KA et al (2019) Social-group-optimization based tumor evaluation tool for clinical brain MRI of flair/diffusion-weighted modality. Biocybern Biomed Eng 39(3):843–856
276. Monisha R, Mrinalini R, Nithila Britto M, Ramakrishnan R, Rajinikanth V (2019) Social group optimization and Shannon's function-based RGB image multi-level thresholding. In Smart intelligent computing and applications (pp. 123–132). Springer: Singapore.
277. Suresh, K., Sakthi, U. (2018) Robust multi-thresholding in noisy grayscale images using Otsu's function and harmony search optimization algorithm. In Advances in electronics, communication and computing (pp. 491–499). Springer: Singapore.
278. Rajinikanth V, Satapathy SC, Fernandes SL, Nachiappan S (2017) Entropy based segmentation of tumor from brain MR images–a study with teaching learning based optimization. Pattern Recogn Lett 94:87–95
279. Razmjooy N, Mousavi BS, Sargolzaei P, Soleymani F (2011) Image thresholding based on evolutionary algorithms. Int J Phys Sci 6(31):7203–7211

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