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

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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.

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 shows 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 (FBIOSO), 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 Nano Tubes (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       |
| 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 |
| 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 | Moghdani 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       |
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.
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
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

| 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               | HBBNO         | 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           |                                                 |                         |
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 |
| 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 |
| 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 |
| 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 |
| 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 |
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                                | Political HIOA | Competitive HIOA | Interactive HIOA | Musical HIOA | Emigrational HIOA |
|----|------------------------------------------------|----------------|------------------|------------------|-------------|-------------------|
| 1  | Cultural Algorithm                             | ×              |                   | ✓                |             |                   |
| 2  | Imperialist Competitive Algorithm              | ×              |                   | x                |             | ✓                 |
| 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                           | ×              |                   | x                |             |                   |
| 17 | Human Urbanization Algorithm                   | ×              |                   | x                |             |                   |
| 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                | ✓              |                   |                   |             |                   |
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.

| 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 | 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 | × | ✓ | × | × |
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 \((C_1, C_2, \ldots, C_i, \ldots C_p)\) using set of (p-1) threshold values \(TH = (t_1, t_2, \ldots, t_i, \ldots t_{p-1})\), where \(t_1 < t_2 < \ldots < t_{p-1}\). For example, \(L = 256\) for an 8-bit image and the grey levels are between 0 and 255 [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:

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

(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 \((C_1, C_2, \ldots, C_i, \ldots C_K)\) using a set of \(n\) threshold point \(T = (th_1, th_2, \ldots, th_j, \ldots th_{K-1})\), 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

\[
T' = \arg \max_{0 \leq T \leq L-1} \{ F(T) \}
\]

(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).

\[
S_q = \frac{1 - \sum_{i=1}^{\infty} \left( p_i \right)^q}{q - 1}
\]

(3)

where, \(0 \leq p_i \leq 1\) 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:

\[
S_q(f + b) = S_q(f) + S_q(b) + (1 - q)S_q(f)S_q(b)
\]  

(4)

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

\[
\begin{aligned}
\{ (p_1, p_2, \ldots, \ldots, p_L) | p_i \geq 0, i = 1, 2, \ldots, L \} \\
L = \text{number of discrete gray levels; } \sum_{i=1}^{n} p_i = 1
\end{aligned}
\]

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:

\[
P_f = \frac{p_1}{p_f^{t}}, \frac{p_2}{p_f^{t}}, \ldots, \frac{p_t}{p_f^{t}} \quad \text{and} \quad P_b = \frac{p_{t+1}}{p_b^{t}}, \frac{p_{t+2}}{p_b^{t}}, \ldots, \frac{p_L}{p_b^{t}}
\]  

(5)

where,

\[
P_f^{t} = \sum_{i=1}^{t} p_i \quad \text{and} \quad P_b^{t} = \sum_{i=t+1}^{L} p_i
\]

(6)

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

\[
S_q^f(t) = \frac{1 - \sum_{i=1}^{t} (p_i/p_f^t)^q}{q - 1}, \quad S_q^b(t) = \frac{1 - \sum_{i=t+1}^{L} (p_i/p_b^t)^q}{q - 1}
\]  

(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:

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

(8)

Subject to the following constraints:

\[
|P_f^t + P_b^t| - 1 < S < 1 - |P_f^t + P_b^t|
\]

where,

\[
S(t) = S_q^f(t) + S_q^b(t) + (1 - q) \cdot S_q^f(t) \cdot S_q^b(t)
\]

(45)

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

\[
(t_1, t_2, \ldots, t_m) = \text{Arg max} \left[ S_q^1(t) + S_q^2(t) + \ldots + S_q^m(t) + (1 - q) \cdot S_q^1(t) \cdot S_q^2(t) \cdot \ldots \cdot S_q^m(t) \right]
\]  

(9)

where,

\[
S_q^1(t) = \frac{1 - \sum_{i=1}^{t_1} (p_i/p_1^t)^q}{q - 1}, \quad \text{and} \quad S_q^m(t) = \frac{1 - \sum_{i=t_1+1}^{L} (p_i/p_M^t)^q}{q - 1}, \quad \text{and} \quad M = m + 1
\]

(10)

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 \( p = (p_0, p_2, p_3, \ldots, \ldots, p_{L-1}) | p_i \geq 0, i = 0, 1, 2, \ldots, L - 1 \) where \( L \) is the number of gray levels in the image I and \( \sum_{i=0}^{L} p_i = 1 \).

Then the t-entropy \( (H_t) \) of the image is computed as the following expression:

\[
H_t(p) = \sum_{i=0}^{L-1} \frac{p_i \tan^{-1} \left( \frac{1}{p_i} \right)}{4}
\]

(12)

where, \( c \) is a positive constant.

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

\[
H^1_t(t_1) = \sum_{i=0}^{d_1-1} \frac{p_i}{w_1} \tan^{-1} \left( \frac{1}{p_i/w_1} \right) - \frac{\pi}{4}
\]

\[
H^2_t(t_2) = \sum_{i=d_1}^{d_2-1} \frac{p_i}{w_2} \tan^{-1} \left( \frac{1}{p_i/w_2} \right) - \frac{\pi}{4}
\]

\[\vdots\]

\[\vdots\]
In 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 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, $NFE = 1,000 \ast d$, 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, $NFE = 1,000 \ast d$, as stopping criterion of the optimization process. For measuring the optimization ability of the HIOAs, mean fitness ($\bar{f}$) and standard deviation ($\sigma$) 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, x64-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 (IHMSM-LIT) | Minimum Cross-Entropy | Esmaeili in the year 2021 [189] | Standard Gray scale images | IHMSM-LIT with PSOM-LIT, FAMLIT, BBOM-LIT, CSM-LIT, GWOM-LIT 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 |
| 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 multilevel 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-SC MFE-BFO | PSNR, MSE and CPU Time | The proposed algorithm shows very good segmentation results in terms of preciseness, robustness, and stability |
| 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. |
| 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 grayscale images | Eight different variants of PLHS with HS | CT, PSNR, Fit\textsubscript{eq} and Fit\textsubscript{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 grayscale 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 grayscale 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 grayscale images | ICA with GA | MSE and PSNR | The proposed algorithm demonstrates the good performance and generated acceptable result |
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.
considering numerous parameters such as fitness function \(f\), standard deviation \(\sigma\), 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 \(\tilde{f}\), Time (sec), FSIM, PSNR and SSIM, PO exhibits the best result whereas HUA attains the best value in terms of \(\tilde{f}\). 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 \(\tilde{f}\), standard deviation \(\sigma\), 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 \(\tilde{f}\) wherein CHIO attains the best \(\sigma\) 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 \(\tilde{f}\) 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 \(\tilde{f}\). Computational time (Time (sec)), FSIM, PSNR and SSIM whereas BRO attains the worst value for standard deviation \(\sigma\). 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 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…

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, | 5                 |
|                             |            | and members in each party           |                   |
|                             | $T_{max}$  | Total number of iterations          | 500               |
|                             | $r$        | Random Number                       | [0,1]             |
|                             | $\lambda$ | 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]             |
|                             | $R'$       | Random Number                       | [-1,1]            |
|                             | $K$        | Controlling diversification and     | 2                 |
|                             |            | intensification of adventurers      |                   |
|                             | $Ripmk$    | Balancing between diversification   | 1                 |
|                             |            | and intensification in searching    |                   |
|                             |            | the city’s boundaries               |                   |
| Particle Swarm Optimization (PSO) | $N$        | Population Size                     | 50                |
|                             | $C_1$      | Acceleration coefficients           | 2                 |
|                             | $C_2$      | Acceleration coefficients           | 2                 |
|                             | $n$        | Population Size                     | 50                |
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 \( \left( \tilde{f} \right) \), standard deviation \( \left( \sigma_f \right) \), 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

\[ \textbf{Fig. 8} \text{ Original color satellite image (Input Image)} \]

\[ \textbf{Fig. 9} \text{ Segmented results of different HIOAs using Tsallis entropy over } nt = 6 \text{ and 8} \]
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 thresholds 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 \( \tilde{f} \), standard deviation \( \sigma_f \), 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

| Number of thresholds (\( nt \)) | HIOA  | \( \tilde{f} \)  | \( \sigma_f \)  | 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

| 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     |
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

| Different Methods | Number of Thresholds($nt$) |
|-------------------|---------------------------|
|                  | $nt = 6$                   | $nt = 8$                   |
| PO                |                           |                           |
| CHIO              |                           |                           |
| HBO               |                           |                           |
| FBO               |                           |                           |
| BRO               |                           |                           |
| HUA               |                           |                           |
| PSO               |                           |                           |

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

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

| Number of thresholds (nt) | HIOAs | $\bar{f}$ | $\sigma_f$ | 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 |
|                           | FBO   | 0.893336  | 3.86E-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 |
|                           | FBO   | 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      | 0.9847 | 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. FBO   | > 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    |
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Declarations

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

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