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Application of a Hybrid Genetic and Hill Climbing Algorithm (HGA) in Metaverse-Based Learning Environments

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Abstract

Metaverse-based learning environments generate large volumes of multimedia data from learner interactions, including eye-tracking, movement patterns, and auditory and behavioural cues. This high-dimensional data presents a computational challenge that impacts the speed and efficiency of adaptive learning systems. This study aims to improve feature selection by proposing a hybrid algorithm that combines genetic algorithms (GA) and hill-climbing algorithms (HCA) to achieve an effective balance between granular search and local optimisation. HCA enhances GA's ability to avoid premature convergence towards local solutions and improves the quality of selected features. The proposed algorithm was evaluated on six standard datasets, and the results showed a significant improvement in classification accuracy with fewer selected features than several established algorithms. In the context of metaverse-based learning, the proposed model reduces the volume of real-time data processed, enables immediate feedback, and improves the efficiency of adaptive analysis systems within immersive learning environments.

1 Introduction:

In recent years, the rise of immersive technologies such as virtual reality (VR), augmented reality (AR), and the metaverse has revolutionised data generation in education and human-computer interaction[1, 2]. These interactive environments continuously generate large, heterogeneous, multimodal datasets, including gaze movements, body motion, voice input, and engagement behaviours. Managing and analysing such high-dimensional data in metaverse-based learning environments presents significant computational challenges, particularly when redundant and irrelevant features reduce the performance and speed of learning algorithms[3, 4].

To address this issue, Feature Selection (FS) techniques have become a fundamental pre-processing step, eliminating irrelevant and redundant data while preserving informative attributes to improve model accuracy and efficiency. In metaverse applications, FS enables machine learning systems to identify critical behavioural or physiological features that indicate learner engagement, cognitive load, and collaboration dynamics. By reducing the number of features, FS enhances not only classification accuracy but also computational time, which is essential for real-time adaptive feedback systems in immersive education.[5]

Traditional methods, such as Blind Search (BS), evaluate all possible feature combinations; however, their exponential complexity makes them infeasible for large-scale metaverse datasets. Hence, heuristic and meta-heuristic algorithms have been adopted to optimise FS efficiently [6]. Among them, the Genetic Algorithm (GA) has proven robust and versatile due to its population-based search and adaptability across problem domains. Genetic algorithms use processes such as selection, hybridisation, and mutation to develop solutions, but they often have difficulty converging early on because local optima are constrained by exploitation.[7, 8].

To overcome this limitation, the Hill Climbing Algorithm (HCA) is introduced as a local optimisation mechanism that enhances GA's performance. HCA permits limited degradation in the quality of the candidate solution, thereby enabling the algorithm to escape local maxima and identify superior feature subsets. The combination of GA and HCA results in a Hybrid Genetic Hill Climbing Algorithm (HGA) that balances exploration (global search) and exploitation (local refinement)[5, 8].

This hybridisation is particularly valuable in metaverse-based learning environments, where adaptive systems must process complex user interaction data in real time[9]. The proposed HGA-based FS framework aims to improve the efficiency of feature extraction from metaverse datasets, such as those involving gaze tracking, movement analysis, or voice patterns, thereby enhancing learner modelling, engagement prediction, and personalisation of virtual learning experiences.

By integrating the exploration power of GA with the exploitation ability of HCA, this study contributes to the development of intelligent data-processing methods for educational metaverse applications[10]. The proposed HGA method offers scalability, improved convergence, and better feature relevance, making it suitable for real-time AI-driven analytics in immersive learning systems.

To simulate a Metaverse-based learning environment, each dataset characteristic can be treated as a behavioural or physiological signal resulting from the learner's interactions within the virtual environment, such as gaze duration, movement speed, number of interactions, or level of vocal participation[1, 11]. Thus, the selection of characteristics represents the selection of the most important indicators of learner behaviour within the immersive environment. See fig.1

Fig.1.*metaverse technology*

2 Methodology

This section provides a detailed description of the hybrid genetic algorithm (HGA) methodology we propose. Genetic algorithms (GAs) are a commonly used optimisation technique but are not fully exploited, as previously mentioned. This affects accuracy by preventing efficient searching near the local optimum, which is unavailable[6, 12, 13]. When the HCA mechanism allows to improve it [13]. Therefore, rather than limiting the use of this method, the goal is to perform a hyperlocal search to reach the global maximum. For this reason, hierarchical clustering analysis (HCA) was used to enhance the local search capabilities of the genetic algorithm (GA).

This integration does not aim to restrict the algorithm's operation, but rather to implement a more efficient local search that ultimately approaches the global optimum. Hence, the name Hill Climb Algorithm (HCA), especially useful when performed within virtual environments that simulate reality, such as the metaverse, to achieve optimal results.

The Genetic Algorithm primarily relies on global search via selection, hybridisation, and mutation. However, its ability to optimise solutions near optimal values remains limited. This deficiency often leads to premature convergence towards suboptimal solutions. In contrast, the Hill Climbing Algorithm provides an intensive local search mechanism that enables subtle, deliberate modifications to the resulting solutions, allowing the acceptance of a small, temporary deterioration in solution quality to escape local peaks and reach better search regions[14].

Accordingly, the hybrid algorithm HGA (Hybrid Genetic Algorithm with Hill Climbing [8]) was proposed, combining the wide-ranging exploration power of GA with the fine-tuning optimisation capabilities of HCA. After hybridisation and the generation of new chromosomes, these solutions are passed to the hill-climbing stage for further local refinement, after which they are evaluated and included in the next generation. This process promotes a balance between exploration and exploitation, a crucial element in high-dimensional feature selection.

In the context of metaverse-based learning environments, where data is complex and multimodal, such as eye-tracking, motion, voice, and behavioural interaction data, this integration provides greater capacity to extract the most relevant features for learner modelling. It also reduces processing time and improves classification accuracy, making it suitable for adaptive learning systems that require immediate responses [1, 15, 16].

Therefore, the use of HGA is not merely a technical improvement over GA, but rather an advanced research framework designed to address local convergence issues and enhance search efficiency in complex learning data spaces within metaverse environments.
From a computational perspective, incorporating the hill-climbing algorithm adds an extra local optimisation stage within each generation of the genetic algorithm[7]. This results in a slight increase in execution time relative to the traditional genetic algorithm, but the increase remains within acceptable limits due to the reduced number of features produced and the subsequent improvement in classification speed. Thus, suitable for adaptive learning applications that require near-instant responses in metaverse environments.

Although standard UCI datasets were used for measurement and replication, future work will expand to real metaverse-based multimedia datasets, including eye-tracking, motion, and voice interaction data, to verify the robustness of the proposed HGA in realistic immersive learning environments.

3 Genetic Algorithm (GA)

The genetic algorithm includes, as well , the conversion of the genetic algorithm from parental chromosomes to offspring chromosomes [13, 17]. The genetic algorithm consists of four essential steps: population generation, parent selection, and information evaluation. Crossover and mutation processes, which mimic biological processes, are integral to chromosomes. The genetic algorithm (GA) begins by generating a set of candidate chromosomes to find optimal solutions. It selects parental chromosomes, then hybridises them to produce offspring chromosomes, which are vectors with values of (0) and (1) indicating whether the chromosome rejects or selects a particular trait [18, 19]. The parental chromosomes are passed on to the next generation. See Fig. 2.

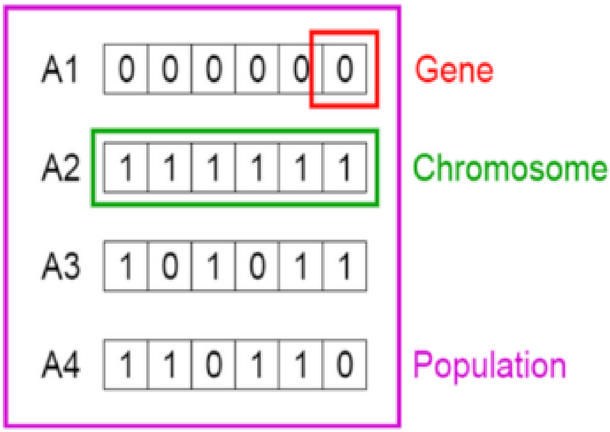

Fig.2 *the switch of the genetic algorithm (Gene, Chromosome and Population).*

However, GA's reliance on random mutations alone to improve local solutions limits exploitation, increasing the likelihood of becoming trapped in local convergence points.

4 Hill Climbing Algorithm (HCA)

In a previous study, HCA [20], This optimisation strategy, that is not accessible from the top [21-23]. To avoid getting wet in increasing rain, you should stand at a higher elevation, see Figure 3, pseudo code is as follows:

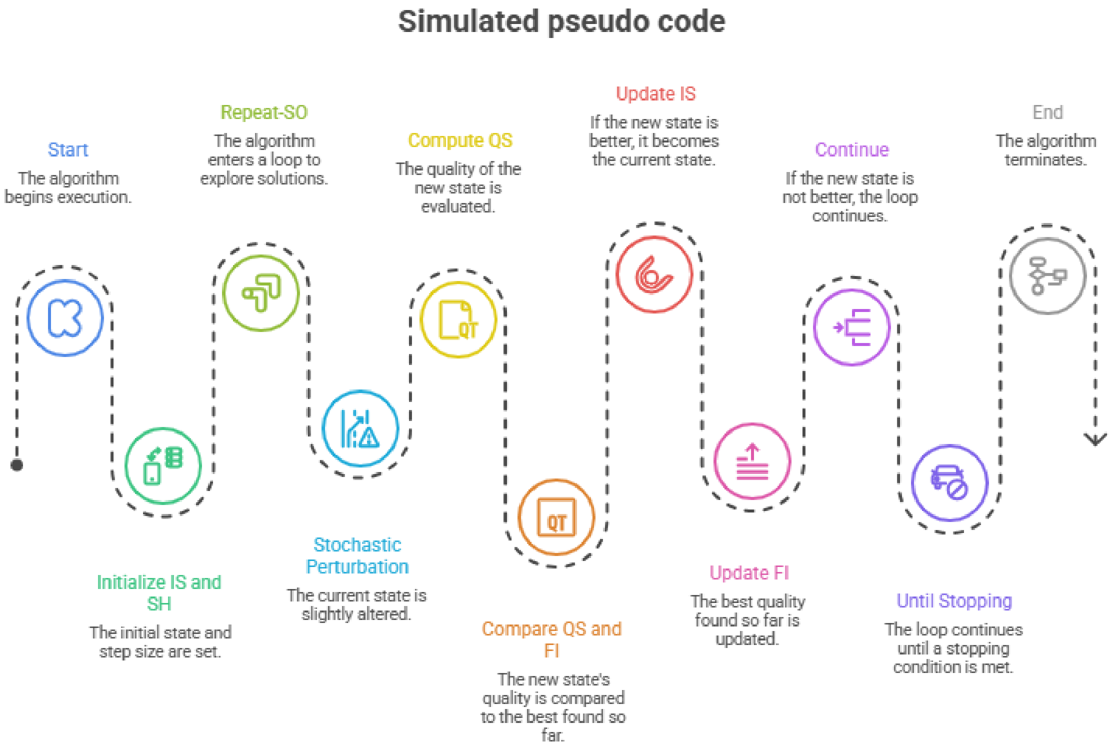

Fig.3 *Steps Hill Climbing Search Algorithm in AI.*

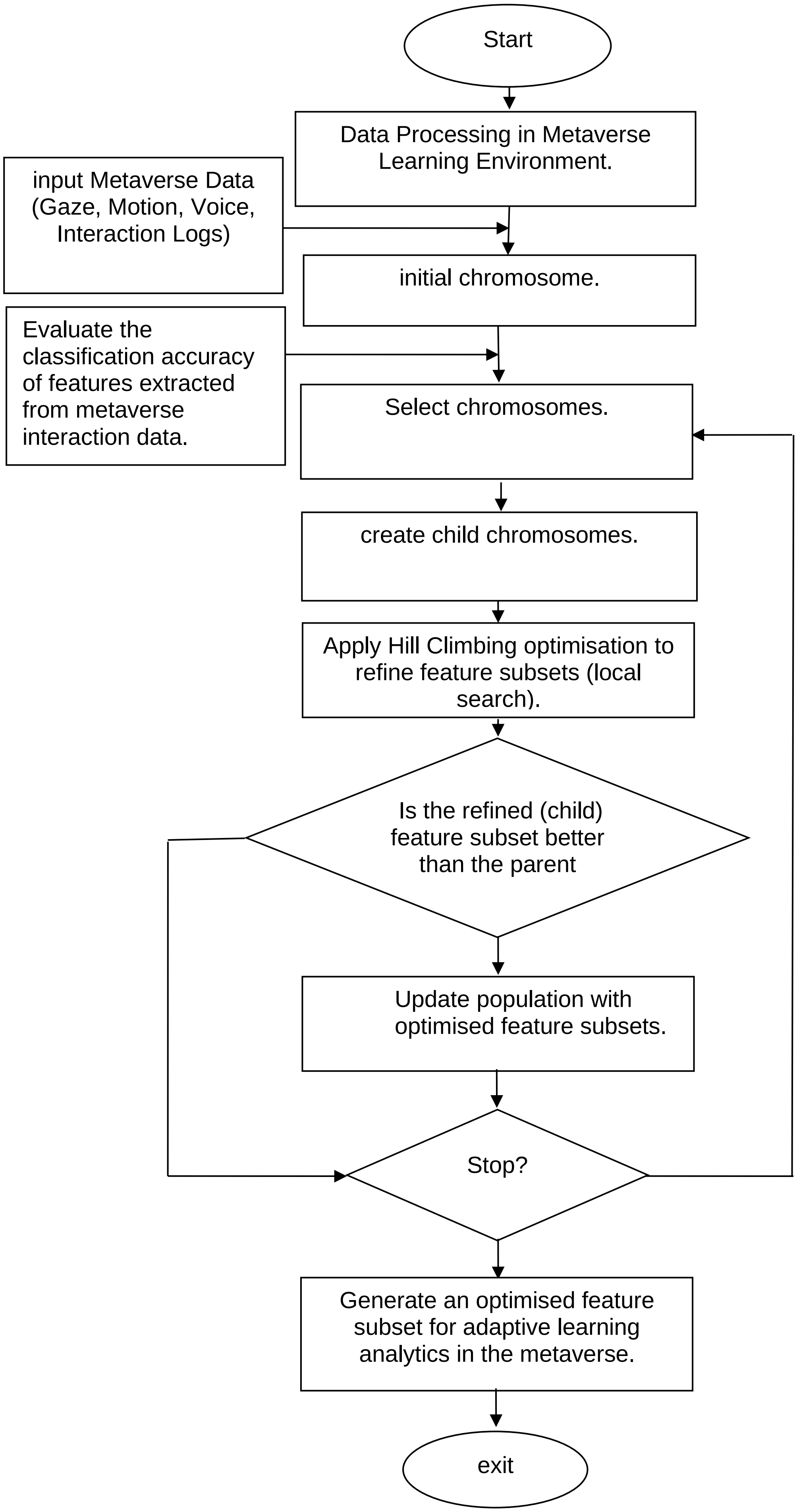

Fig. 4. *Flowchart of the Hybrid Genetic–Hill Climbing Algorithm (HGA) for Feature Selection in Metaverse-Based Learning Environments.*

Principal Component Analysis (HCA) indicates a decline in the quality of solutions that were previously considered for achieving a new, higher value that would have been impossible to reach otherwise. This characteristic has been incorporated into our proposed strategy for enabling effective local research [23].HCA is characterised by its ability to make subtle improvements to solutions; however, when used alone, it may fail to explore the vast search space, which justifies its integration with GA.

After mating, the resulting chromosomes are evaluated using the HCA algorithm to perform a local search.

5 Hybrid Genetic Algorithm with Hill Climbing (HGA)

The proposed solution, HGA, combines HCA and GA to address the difficulties associated with simple GA, including gene transfer and GA between parental and child chromosomes.[14, 23]. GA comprises four main steps: data analysis, parent selection, crossover, and population initialisation[8]. To overcome this problem, the GA-generated child chromosomes are stochastically disrupted using HCA, thereby helping them avoid local maxima. Figure 1 depicts the flowchart of the proposed model. It is chosen that the maximum number of iterations will be 20[24].

This integration achieves a complementary balance in which GA explores new regions of the solution space[25], while HCA refines promising solutions locally. This interaction reduces the risk of premature convergence and increases the likelihood of achieving near-perfect solutions[26].

5.1 Population creation

Initially, a randomly generated set of chromosomes is created, consisting of a series of zeros and ones, where 1 represents a selected trait and 0 represents an ignored trait. Each chromosome represents a subset of traits. Consequently, chromosomes are integer vectors with values ranging from 0 to 1. The primary goal of the algorithm is to identify the optimal chromosome, and the population size is assumed to be 20[27].

5.2 Selection parent

The GA searches for specific paternal chromosomes after generating a set of chromosomes for hybridisation. This selected the paternal chromosomes using a roulette wheel selection method [8, 28]. The chromosome with the highest resolution is given more space on the wheel [29]. The probability of selecting the best chromosomes with the largest gaps increases. The roulette wheel selection technique proceeds as follows: two parental chromosomes are selected, then mating occurs, and so on. [22, 30].

5.3 Crossover

Gene exchange occurs between selected parental chromosomes because regular gene exchange is better than single-point gene exchange [29, 30]. This method is implemented by flipping a coin with probability 0.5. In the end, ultimately, the child's chromosomes are a homogeneous mixture of genetic information from both parents. See Figure 5.

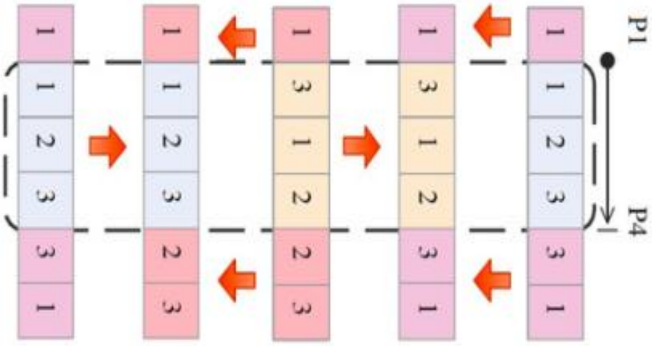

Fig 5. *An example of an occurrence between the chosen parent chromosomes[8].*

5.4 Replacement child

Finally, the child's chromosomes are added to the collection rather than the parents' chromosomes, and are passed on to the next generation if the child's classification accuracy exceeds that of the parents'; otherwise, the parents remain.[29, 31].

6 Analysis and Results

This section presents the results of the HGA algorithm on several datasets. This study verified the feasibility of the proposed technique by comparing these results with those of several modern algorithms. Notably, the HCA algorithm outperforms the GA algorithm in terms of accuracy and requires fewer parameters, despite its higher computational cost. Therefore, the practical application of the HCA algorithm is demonstrated in comparison with the GA algorithm. This section includes a description of the datasets used in this study, a description of the classifier, and an analysis of the results. The results indicate that the HGA algorithm achieved higher accuracy across most datasets than the other algorithms, while reducing. This reflects the algorithm's ability to exclude irrelevant features while maintaining the model's discriminatory capacity.

7 Dataset description

The study selected 6 datasets from the University of California, machine learning repository, to evaluate HGA[32, 33].The number or attributes in these datasets can be classified into three categories: small, medium, and large.

Reducing the number of features selected by HGA indicates the algorithm's ability to identify the most important interaction indicators within immersive learning environments[34]. In the context of the Metaverse, this can involve identifying the most significant behavioural variables affecting learner engagement, such as gaze patterns or interaction intensity, thereby reducing the processing load on real-time analysis systems within virtual environments.

8 Classifier description

To assess the accuracy of the classification of candidate solutions generated from HGA, we used three standard methods: Linear Search Algorithm (LSA), Feedforward Neural Network (FNW), and Simple Bayesian Algorithm (NB) [35, 36]. The fitness values of the chromosomes determined using these classifiers indicate their correctness.

The results of the proposed technique are independent of the classification model, making HGA more compatible with different platforms.

Table 1. The classification of small, medium, and large and information from UCI datasets were used in the experiments.

Small	Thyroid	TH	5	215	3
	Iris	IR	4	150	3
Medium	Dermatology	DE	34	358	6
	Credit-a	CR	14	690	2
Large	Spctrometer	SP	102	531	2
	Hill valley	HV	101	606	2

Table 2. Optimal for the critical parameters (K for KNN, No. of neurons,FFNW, and Kernel, NB) of the classifier models used in the experimentation over different .

Dataset classifier	KNN Value of K	FFNW N0. Neurons in the hidden layer	NB Kernel
TH	3	70	
IR	3	50	
CR	4	160	
DR	11	90	
SP	4	90	Polynomial
HV	9	150	

This study determines the optimal evaluation environment for the candidate solutions. Table 2 shows the best-performing parameter combinations for the classifiers. The comparison indicates that HGA outperforms other optimisation techniques across six datasets. This clearly demonstrates the feasibility of using HGA for data search.

Table 3. *Precision obtained after FS by HGA using 3 classifiers (KNN, FFNW, NB) over 6 datasets.*

Dataset						
	KNN		FFNW		NB	
Dataset classifier	Accuracy (%)	Number of features	Accuracy (%)	Number of features	Accuracy (%)	Number of features
TH	98,20	4	99.50	135	99.50	4
IR	98.40	4	100.00	3	100.00	3
CR	96.8	16	99.6	17	96.3	18
DE	90.2	8.5	92.5	7	89.5	7
SP	59.8	55	60.7	50	78.12	89
HV	61.5	243	63.2	236	62,10	239

Table4. accuracy obtained by proposed FS model HGA,that of GA, ACO, NN and HMOGA using KNN classifier in this comparison.

Dataset	HGA		GA		ACO		NN		HMOGA	
	Number Of Features	Accuracy (%)	Number Of Features	Accuracy (%)	Number Of Features	Accuracy (%)	Number Of Features	Accuracy (%)	Number Of Features	Accuracy (%)
TH	4	98.2	4	91.9	4	98.10	3	73.10	4	95.00
IR	4	98.4	6	86.2	7	73.3	4	55.9	3	99.10
CR	16	96.8	25	96.3	19	96.1	19	91.70	18	96.2
DE	8.5	90.2	7	86.1	8	83.1	8	81.1	4	56.20
SP	55	59.8	212	62.7	159	62.9	142	59.10	123	60.9
HV	243	61.5	73	55.2	71	56.31	40	52.3	55	61.3

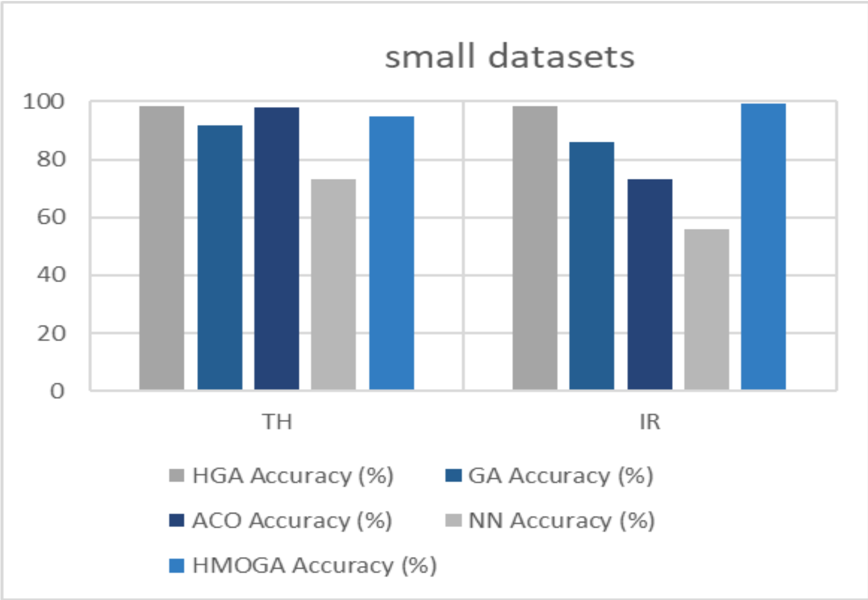

Fig. 6. *obtained by HGA with that of GA, ACO and HMOGA over small classification datasets.*

Figures 6, 7, 8, 9, 10, and 11 present a comparison between HGA data and other methods, the diversity of features and accuracy across datasets. Figures 2, 3, and 4 present the accuracy achieved by several FS algorithms on respective datasets. Similarly, Figures 8, 9, and 10 data illustrating the proportion of features selected by the model to obtain the best solution across small, medium, and large datasets.

9 Discussion

The results indicate that the HGA hybrid algorithm achieved an effective balance between exploration and exploitation, thereby avoiding the local convergence problem inherent in traditional genetic algorithms. This balance resulted in the selection of smaller feature sets while maintaining high classification accuracy, demonstrating the algorithm's efficiency in handling high-dimensional data. For example, in the Metaverse learning platform, hundreds of signals are collected from motion, eye, and voice trackers. The HGA application allows selection of a limited set of signals that are most influential in determining the student's level of engagement, enabling the system to provide immediate feedback without computational delay.

However, the use of standard datasets instead of real data from Metaverse learning environments is one of the limitations of the study, which calls for verifying the model's effectiveness on multimedia data in future studies.

10 Conclusion

The lack of exploitation for GA, on the other hand, has an impact on its population. This study presents a hybrid algorithm combining GA and HCA to address the local convergence problem in feature selection. The results demonstrate a significant improvement in accuracy and a reduction in the number of selected features compared to several standard algorithms. This work highlights the importance of integrating global exploration with local optimisation in processing high-dimensional data, particularly in immersive learning applications based on the Metaverse.

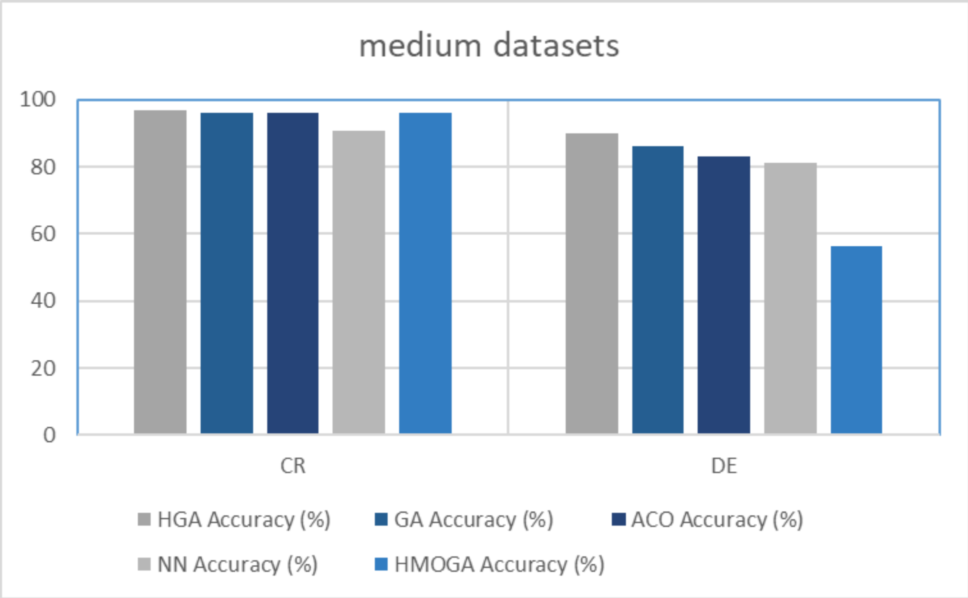

Fig. 7 *The accuracy obtained by HGA, classification accuracy of GA, ACO, and HMOGA on intermediate.*

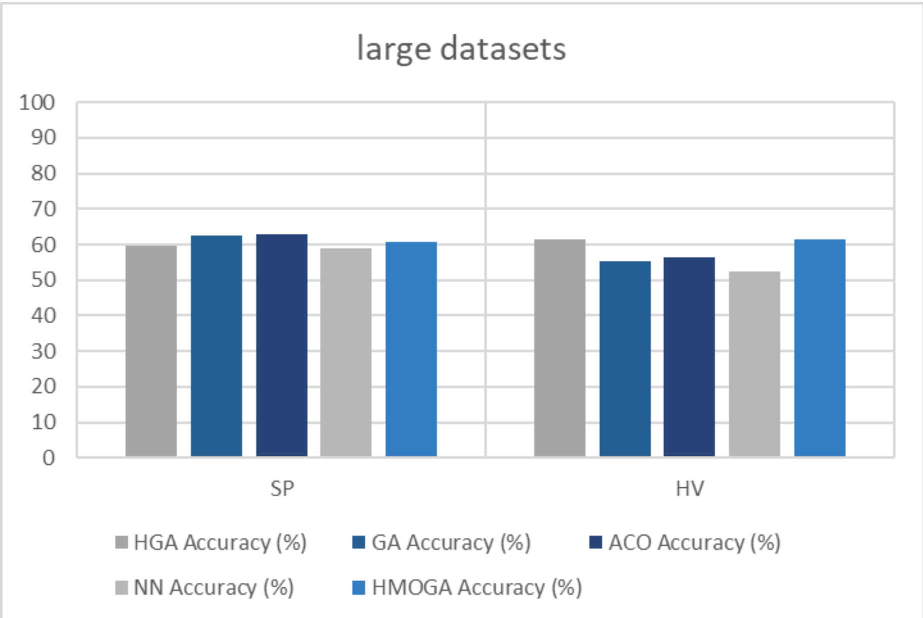

Fig. 8 *Comparing the classification accuracy obtained by HGA with the accuracy of GA, ACO and HMOGA on large classification datasets.*

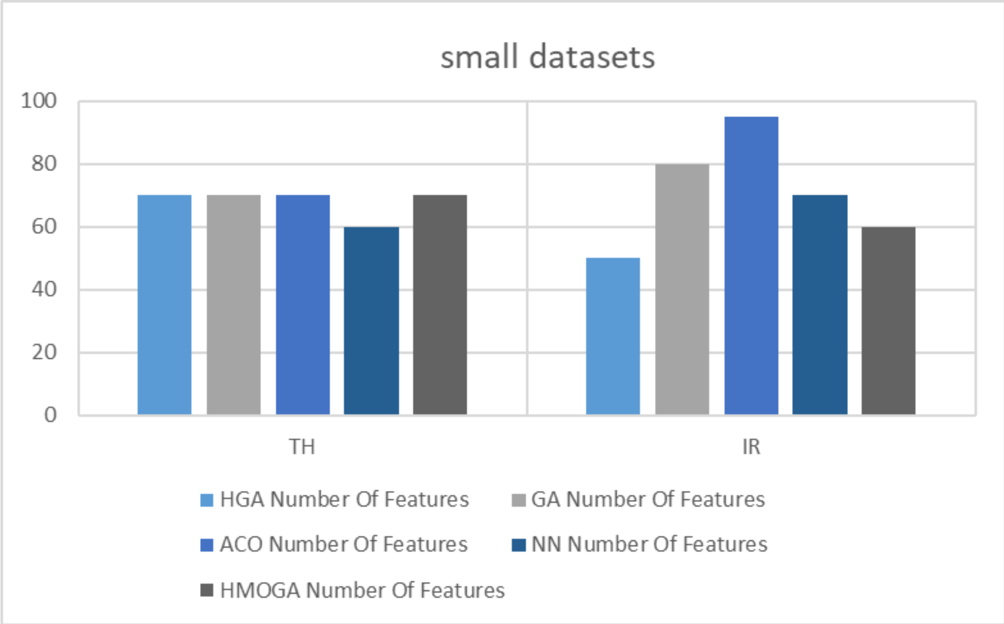

Fig. 9 *Comparing the proportion of features selected, HGA with those of GA, ACO, and HMOGA on small classification datasets.*

Therefore, the macro model outperforms the simple genetic algorithm in finding the global optimum. Because the hierarchical clustering algorithm (HCA) is relatively simple.

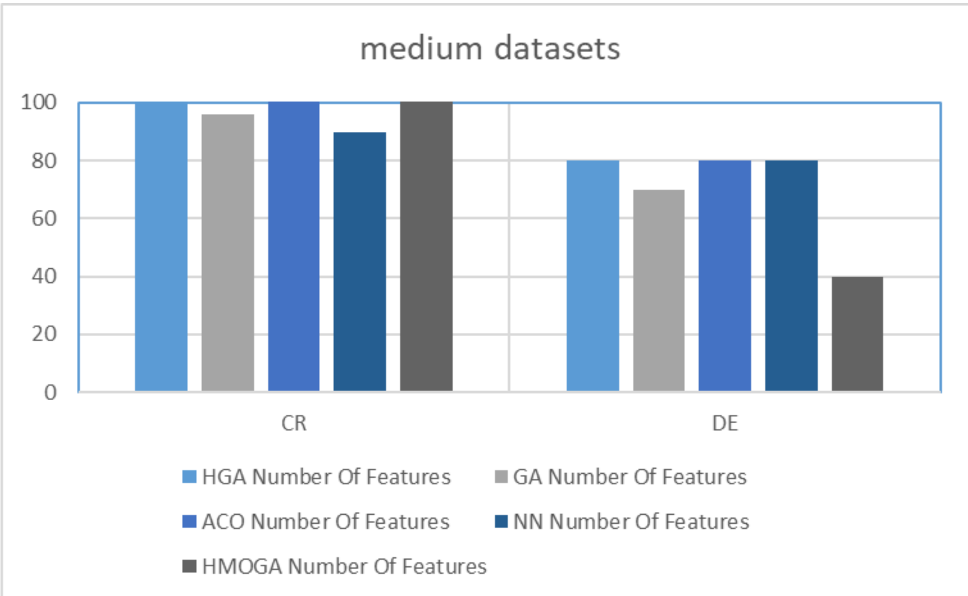

Fig. 10 *Comparison ratio of features selected by HGA with that of GA, ACO and HMOGA over medium classification datasets.*

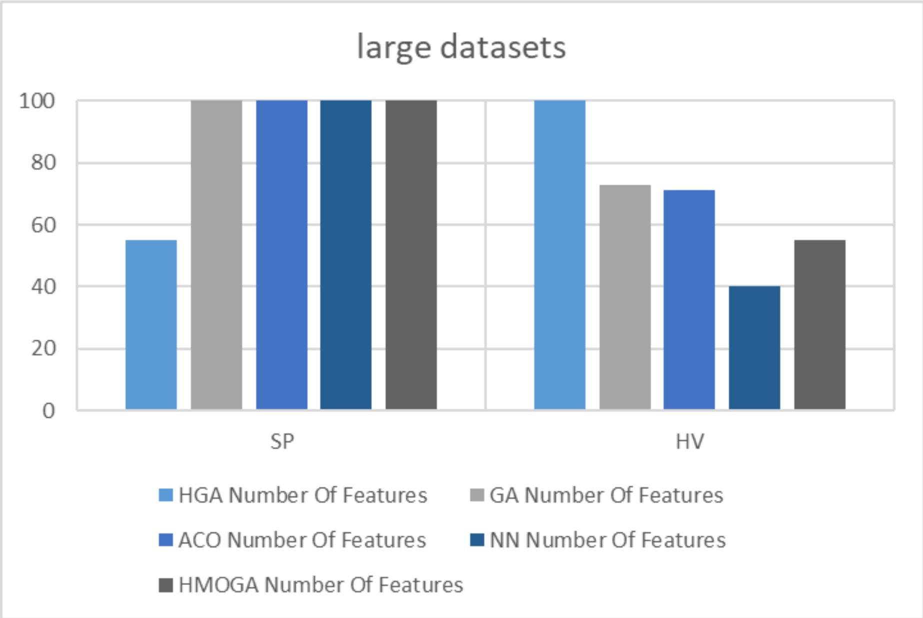

Fig. 11 *Comparison ratio of features selected by HGA with that of GA, ACO and HMOGA over large classification datasets.*

Searching technique and use it for other methods, which also suffer from the same exploitation problem as GA. The use of HGA for more application-based FS can also be explored. The results demonstrate that combining local and global searches enhances feature selection efficiency in high-dimensional environments[14]. HGA's superior performance stems from its ability to balance exploration and exploitation effectively. However, its reliance on standard data and the lack of a time-complexity analysis are limitations that must be considered. In the context of metaverse-based learning, the proposed algorithm reduces the volume of multimedia data processed in real time, thereby enhancing the efficiency of adaptive learning systems and enabling immediate responses to learner interactions within virtual environments.

11 Limitations

The current study is limited to standard datasets and does not include real data from Metaverse learning environments. Furthermore, no time complexity analysis or statistical significance tests were performed, which limits the generalizability of the findings.The current study did not include a detailed analysis of time complexity and runtime. Statistical significance tests, such as paired t-tests or Wilcoxon signed-rank tests, will be used in future studies to verify whether the observed performance improvements are statistically significant.However, future studies will provide a comparative assessment of the computational cost to evaluate the scalability of the HGA algorithm in real-time adaptive learning systems.Despite its effectiveness, the proposed HGA framework suffers from several limitations, including reliance on standard datasets, lack of runtime analysis and statistical significance, and limited classifier diversity. Addressing these limitations in future research will enhance the model's applicability, scalability, and real-world relevance, particularly within Metaverse-based adaptive learning systems.

12 Future Work

Future research suggests applying HGA to real-world data from virtual learning platforms, including eye-tracking, motion, and voice interaction data. A comparative time-based analysis is also recommended, along with an examination of the impact of algorithm parameters such as community size and number of iterations on performance.Future studies will include sensitivity analysis to examine the impact of key parameters such as group size, crossover probability, and number of iterations on performance stability.To enhance generalizability, future work will expand the scope of the assessment to include additional classifiers such as supporting vector machines and crowdle learning models.Future HGA applications will be integrated into live Metaverse learning platforms to directly measure their impact on learner engagement, feedback response time, and adaptive personalization.(Hybrid Metaheuristics),Subsequent studies will compare HGA with modern hybrid and interpretable feature selection methods to further validate its competitive advantage.

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تطبيق خوارزمية هجينة تجمع بين الخوارزمية الجينية وخوارزمية تسلق التلال في بيئات التعلم القائمة على الميتافيرس

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الخلاصة:

تُنتج بيئات التعلم القائمة على الميتافيرس كميات هائلة من بيانات الوسائط المتعددة من تفاعلات المتعلمين، بما في ذلك تتبع حركة العين، وأنماط الحركة، والإشارات السمعية والسلوكية. تُشكل هذه البيانات عالية الأبعاد تحديًا حسابيًا يؤثر على سرعة وكفاءة أنظمة التعلم التكيفي. تهدف هذه الدراسة إلى تحسين اختيار الميزات من خلال اقتراح خوارزمية هجينة تجمع بين الخوارزميات الجينية (GA) وخوارزميات تسلق التلال (HCA) لتحقيق توازن فعال بين البحث الدقيق والتحسين المحلي. تُعزز خوارزمية تسلق التلال قدرة الخوارزميات الجينية على تجنب التقارب المبكر نحو الحلول المحلية، كما تُحسّن جودة الميزات المختارة. تم تقييم الخوارزمية المقترحة على ست مجموعات بيانات قياسية، وأظهرت النتائج تحسنًا ملحوظًا في دقة التصنيف باستخدام عدد أقل من الميزات المختارة مقارنةً بالعديد من الخوارزميات المعروفة. في سياق التعلم القائم على الميتافيرس، يُقلل النموذج المقترح من حجم البيانات المُعالجة في الوقت الفعلي، ويُمكّن من الحصول على تغذية راجعة فورية، ويُحسّن كفاءة أنظمة التحليل التكيفي ضمن بيئات التعلم الغامرة.