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Automatic classification and storage method of electronic medical records based on improved genetic algorithm

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ABSTRACT

This paper gives an automated category and storage method for electronic clinical records utilizing an stepped forward genetic set of rules (IGA). Effective management of digital medical facts is fundamental to medical informatization. But, the sheer extent and complexity of statistics render traditional guide classification and storage methods insufficient. To deal with this assignment, the paper first opinions present EMR type and storage techniques, encompassing rule-based and facts-primarily based techniques, and evaluates their deserves and boundaries. In the end, it introduces the genetic set of rules as an optimization technique, illustrating its various applications throughout various domains. Building upon this foundation, the paper proposes an IGA tailored to the unique characteristics of EMRs. The improvements encompass person coding, fitness characteristic format, and optimization of genetic operations. Via empirical validation, the proposed method demonstrates superior overall performance in EMR category and garage obligations, boasting stronger accuracy and efficiency as compared to existing methodologies. This studies offers a novel answer for EMR control, thereby advancing the progress of medical informatization.

Keywords: IGA, digital scientific information, computerized classification storage, clinical informatization

1. Introduction

Electronic medical information (EMRs) represent a vital aspect of clinical informatics [1-3], taking pictures necessary facts together with patients' medical histories [4-5], diagnoses, and treatment plans [6-7], that are pivotal for boosting the high-quality of scientific offerings and facilitating clinical decision-making. But, the non-stop enlargement [8-10] and complexity of clinical facts pose numerous challenges to EMR control.

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Primarily, the sheer volume of EMR records renders manual processing exhausting. Traditional guide type and garage techniques [11-12] show inefficient and liable to human subjectivity, main to problems like faulty type and negative consistency. Moreover, the diversity and intricacy of EMR records [13-15] present hurdles for automatic class and storage. Facts can also encompass diverse codecs including textual content, pictures, physiological parameters [16], necessitating powerful type and storage strategies.

Addressing these challenges necessitates urgent adoption of automated type and garage methods. Leveraging computer science and artificial Genius, specially system studying techniques, allows automatic processing and shrewd management of EMR data. Among these techniques, genetic set of rules (GA) [17-19], as optimization algorithms, exhibit strong worldwide search abilities and flexibility, finding vast use in various optimization domain names consisting of engineering and machine learning version parameter optimization.

Gasoline simulate natural evolutionary procedures [20-21], exploring solution areas thru population evolution and genetic operations. Their parallel search functionality and adaptability render them powerful in optimizing complex, excessive-dimensional problems. Therefore, making use of fuel to EMR automatic class and storage promises to address present methodological barriers, improving type accuracy and performance.

This text delves into an automatic class and storage approach for EMRs primarily based on an IGA. It first elucidates the importance and demanding situations of EMRs, highlighting boundaries of contemporary processes. Ultimately, it underscores the indispensable and extant challenges of computerized category and garage, introducing GA programs. Subsequently, it offers a succinct evaluate of GA concepts and programs in optimization issues, envisioning its ability price in EMR class and garage.

2. Related Works

Within the area of scientific informatics [22-24], the automated class and garage methodology of electronic scientific records has garnered full-size attention and studies efforts. Current processes predominantly encompass rule-primarily based and facts-based totally methodologies [25-27]. Each methodology famous wonderful benefits and drawbacks, necessitating a complete evaluation to clarify current challenges and avenues for enhancement.

The guideline-based totally method is some of the earliest strategies adopted for classifying and storing electronic clinical facts. This approach includes manual formulation of classification rules grounded in keywords or specific patterns identified within clinical records. These guidelines can also involve diagnostic tags, key-word matching, textual content similarity metrics, and so forth.

The primary advantage of the rule of thumb-primarily based technique lies in its intuitive and understandable nature, facilitating ease of implementation and clarification. Rules may be devised primarily based at the understanding of clinical practitioners [28-30], ensuring a sure diploma of accuracy.

But, the rule of thumb-primarily based approach suffers from boundaries such as loss of versatility, necessitating various policies for various scientific report types and scientific eventualities, thereby incurring high renovation charges. In complicated clinical report contexts, these guidelines might also show inadequate in accuracy or insurance.

Contrarily, statistics-primarily based methodologies utilize system mastering strategies to assemble type models by using gaining knowledge of from great datasets of classified digital scientific statistics. Not unusual statistical strategies embody Naive Bayes, help Vector device (SVM), choice Tree, and so on.

Information-based methodologies offer the benefit of automatically learning features and styles from records, exhibiting positive generalization skills. They’re suitable for complex classification scenarios, gifted in coping with multi-category and multi-dimensional type duties.

But, those methodologies are vulnerable to overfitting or underfitting troubles in eventualities with limited facts or sparse features. They necessitate extensive classified education facts, entailing excessive prices for facts education and annotation.

As an optimization algorithm, GA have observed successful utility throughout numerous domains. They emulate the system of natural evolution, seeking ultimate answers through operations like choice, crossover, and mutation. In fields like optimization trouble solving, gadget learning version parameter optimization, and image processing [31-33], GA have yielded promising results.

Specially within the realm of electronic medical report category and storage, GA preserve promise for reinforcing accuracy and performance. with the aid of tailoring person illustration and coding schemes, designing appropriate health functions, optimizing genetic operations, and thinking about multi-goal optimization, GA are poised to deal with the inherent complexities of medical record classification and storage.

In conclusion, current methodologies for digital medical document type and garage exhibit limitations warranting similarly refinement. Leveraging GA gives a pathway to mitigate these obstacles and raise the precision and efficacy of classification, thereby fostering improvements in clinical informatics.

3. Method

3.1. GA

The GA represents a bio-inspired approach simulating the evolutionary manner of existence. As depicted in Fig. 1, the GA begins with a random initial populace and proceeds through choice, crossover, and mutation levels, guiding the population toward a favored evolutionary course. Every character genotype within the population is encoded as a binary string.

On this have a look at, the GA is configured with an preliminary population length of 50 people, each possessing a genotype length of nineteen after experimentation. The maximum number of iterations is capped at 100, employing the roulette method for selection and two-point crossover with a crossover probability of $p = 0.6$. Additionally, random mutation of row positions occurs with a probability of $p = 0.01$. The recognition accuracy outputted by the category recognition model serves as the fitness function value. The iteration terminates upon reaching the maximum number of iterations or achieving a recognition accuracy of 100%.

By adhering to the standards of scientific publications, this refined description of the GA's implementation highlights its evolutionary nature and methodical approach towards data screening. Moreover, it clarifies the parameters and procedures involved in the GA, ensuring clarity and precision in conveying the research methodology.

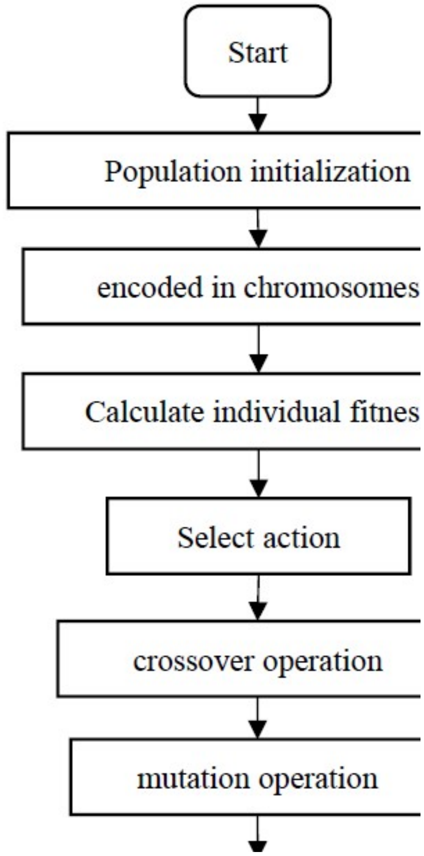

Fig. 1. GA flow chart

3.2. IGA

Figure 2 illustrates the flowchart detailing the IGA. By integrating local search operators into the selection step of GA, the algorithm's ability for global exploration is significantly augmented, thereby mitigating issues related to premature convergence and local optima trapping. Notably, a local search operator grounded on superior patterns is employed. Initially, a subset of individuals exhibiting fitness values surpassing the population's average is chosen to derive a good pattern. Subsequently, a locally optimal solution proximal to this good pattern is generated. The resultant local optimal solution is then juxtaposed against the current optimal solution. Should the fitness value and sample length of the generated solution outperform those of the current population's optimal solution, the newly generated solution supersedes the incumbent optimal solution.

This refinement strategy integrates local search mechanisms within the GA, enhancing its capacity to navigate solution spaces effectively. By judiciously leveraging local information gleaned from superior patterns, the algorithm ensures a more comprehensive exploration of the search space, thereby circumventing premature convergence and achieving improved convergence to global optima.

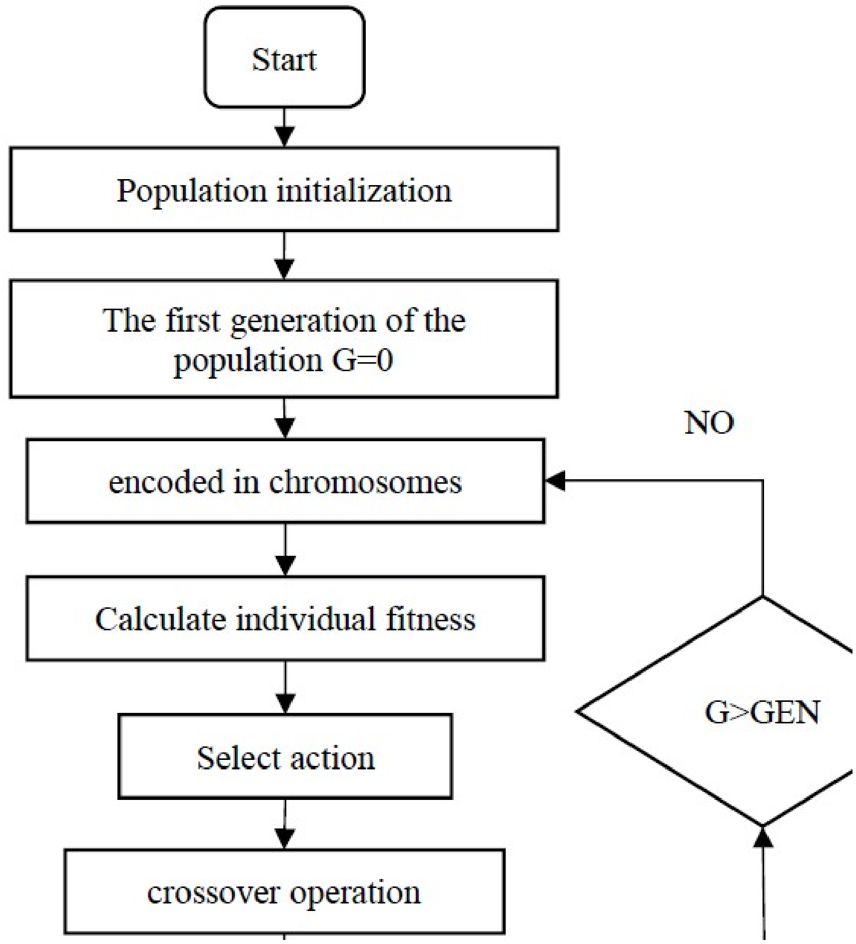

Fig. 2. IGA flow chart

The design of the local search operator is structured as follows:

Step 1: Generation of Promising Patterns

1) Initial Calculation of the Number of Improvements n_i at Each Gene Position within the Superior Population:

$$n_i = \sum_{j=1}^{\alpha \cdot n} x_{ij} \tag{1}$$

2) Utilization of Prescribed Rules to Generate Exceptional Models.

Step 2: Generation of Local Optimal Solutions

Extraction of the Optimal Solution from the Superior Population.

Random Generation of an Optimal Solution ' h ' within Close Proximity to an Exceptional Model.

If the Fitness of Individual ' h ' Surpasses the Fitness of Individual z, Replace z with h.

If $k \geq n$ is reached, Terminate and Output the Local Optimal Solution. Otherwise $k = k + 1$, Proceed to the Next Iteration.

Step 3: Utilization of the Local Optimal Solution to Substitute the Individual with the Lowest Fitness Value within the Current Population.

Due to the incorporation of a mechanism for retaining locally optimal individuals, we introduce the definitions ofsimilarityand concentration as follows:

Definition 1: Similarity

In the context ofbinary GA, the similarity between two individuals oflength n is formally defined as Equation (2) in the paper.

$$s(x,y)=\frac{l-\sum_{i=1}^{l}|x_i-y_i|}{l} \tag{2}$$

Definition 2: Concentration

In the binary GA, the population size is denoted by n , and the concentration of any individual x is defined as:

$$c(x)=\frac{Q(x,y)}{l} \tag{3}$$

The hybrid selection mechanism based on fitness and concentration consists of several steps, outlined as follows:

Step 1: Calculation of Selection Probabilities

Firstly, the selection probability of each individual within the group is calculated based on their fitness values, as described by Equation (4).

$$p(x_i)=\frac{F(x_i)}{\sum_{k=1}^{n}F(x_k)} \tag{4}$$

The selection probability of each individual based on its concentration value, as shown in Equation (5),

$$p_c(x_i)=\frac{1-c(x_i)}{n-\sum_{k=1}^{n}c(x_k)} \tag{5}$$

Step 2: Calculate the mixed selection probability of each individual in the population based on fitness value and concentration value.

$$p(x_i)=\mu\cdot p(x_i)+(1-\mu)p_c(x_i) \tag{6}$$

Step 3 Use $p(x_i)$ as probability to guide roulette selection and generate new individuals.

Table 1 shows the pseudo code of the IGA.

Table 1. IGA

Algorithm 1: IGA for Optimization
Input: Problem-specific parameters and constraints
Output: Optimized solution
Initialize Population with Random Solutions
Evaluate Fitness of Each Solution
while not Termination Condition do
Select Parents for Crossover
Perform Crossover Operation to Create Offspring
Perform Mutation Operation on Offspring
Evaluate Fitness of Offspring
Select Survivors for Next Generation
Apply Selection Pressure Mechanism (e.g., Elitism, Tournament Selection)
Update Population with Survivors
end while
return Best Solution Found

3.3. Data set

This dataset originates from the medical information system of a hospital. It covers patients of diverse demographics, including different ages and genders. Rigorous anonymization measures have been applied to safeguard patient privacy.

Each entry in the dataset represents a patient's electronic medical record, comprising essential details such as patient ID, age, gender, visit timestamp, and auxiliary examinations. Those statistics provide a comprehensive view of sufferers' clinical histories and remedy trips.

The dataset boasts several gorgeous traits:

Range: With its coverage spanning multiple departments and encompassing numerous sorts of medical facts, the dataset gives insights into the remedy landscape throughout a spectrum of sicknesses inside the health center.

Practicality: rich in scientific records, the dataset serves as a precious resource for numerous scientific statistics mining duties, which includes ailment prognosis, treatment layout optimization, and medical occasion prediction. Its wealth of records enables researchers and practitioners to explore and address a big range of healthcare challenges.

Anonymization: Stringent anonymization protocols had been hired to make certain the confidentiality of affected person statistics. By anonymizing in my view identifiable details, the dataset maintains compliance with privateness rules whilst nonetheless facilitating valuable studies endeavors.

In summary, this dataset not solely gives a wealthy and varied aid for scientific studies but also prioritizes patient privacy through powerful anonymization measures. Its breadth and intensity make it a useful asset for advancing healthcare research and practice in numerous domains.

Information normalization processing

$$y_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{7}$$

True rate

$$TPR = \frac{TP}{TP + FN} \tag{8}$$

False positive rate

$$EPR = \frac{FP}{FP + TN} \tag{9}$$

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

4. Experiment Results

4.1. Assessment System

Table 2 provides a comparative analysis of the adaptability between the GA) and the IGA. The exam of Table 2 reveals noteworthy differences in the common populace fitness and most fitness values, favoring the IGA. These findings advise that the IGA well-knownshows heightened operational efficiency, yielding more specific, reliable, and effective experimental results.

The method elucidated in this paper takes into complete consideration the destructive impact that excessively simplistic or overly complex fitness calculations may have on algorithmic optimization performance. As a result, in computing fitness, pragmatic concerns are factored in, and the goal function is meticulously formulated to beautify health adaptability. This meticulous method no longer solely enhances the adaptability of the health function but also contributes to the general robustness and efficacy of the algorithm.

Table 2. Fitness comparison results of GA and IGA

Population	GA		IGA	
	Fitness average	Maximum fitness value	Fitness average	Maximum fitness value
Initial population	0.0366	0.0545	0.0414	0.0655
New generation 1 population	0.0388	0.0557	0.0425	0.0686
New generation 2 population	0.0326	0.0437	0.0460	0.0695
New generation 3 population	0.0383	0.0512	0.0472	0.0645
New generation 4 population	0.0322	0.0553	0.0465	0.0675
New generation 5 population	0.0359	0.0560	0.0476	0.0634
New generation 6 population	0.0355	0.0556	0.0472	0.0656
New generation 7 population	0.0356	0.0554	0.0436	0.0666
New generation 8 population	0.036 6	0.0510	0.0440	0.0658
New generation 9 population	0.035 4	0.0520	0.0445	0.0622
New generation 10 population	0.0343	0.0534	0.0469	0.0646
New generation 11 population	0.0356	0.0569	0.0468	0.0667
New generation 12 population	0.0377	0.0523	0.0455	0.0689

4.2. Experiment Results

On this segment, we undertaking to conduct an exhaustive assessment between the classic GA and the improved IGA, meticulously studying various overall performance dimensions. Through an in-intensity exploration of both algorithms concerning accuracy, convergence speed, balance, and flexibility, we purpose to offer comprehensive insights into their respective strengths and limitations, thereby facilitating a really apt choice of the most appropriate algorithm.

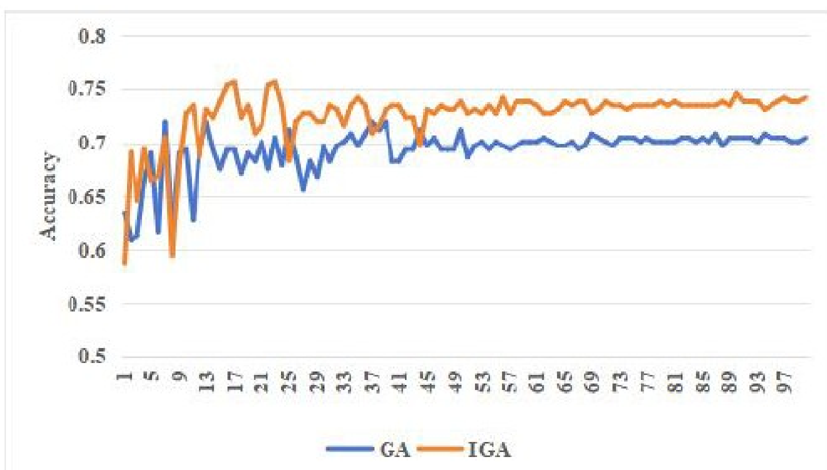

Fig. 3. Accuracy changes with the number of iterations

As depicted in Figure 3, the accuracy tendencies of each the GA and IGA algorithms exhibit discernible styles because the quantity of iterations progresses. Whilst both algorithms take place a slow enhancement in accuracy over the iteration cycles, nuances of their overall performance end up apparent at numerous tiers of iteration.

Initially, the traditional GA demonstrates an accuracy of about 0.63. With the successive increase in iterations, there is a steady uptick in accuracy, albeit at a relatively subdued pace, culminating at around 0.70. Nonetheless, despite the observed improvement, the augmentation in accuracy appears incremental, and the algorithm tends to stabilize during later iterations, converging to a plateau around the 0.70 mark.

In stark contrast, the accuracy of the IGA starts from a lower level in the initial stages. However, as the iteration count escalates, there is a discernible acceleration in accuracy, swiftly closing the gap with the classic GA and eventually surpassing it in later iterations. Particularly noteworthy is the observation that post approximately 50 iterations, the accuracy of the IGA eclipses the 0.70 threshold, stabilizing at approximately 0.73 in subsequent iterations, indicative ofa relatively rapid convergence trajectory.

In synthesis, while both algorithms exhibit efficacy in enhancing accuracy, the IGA showcases swifter convergence and attains higher accuracy levels within comparable iteration counts. This underscores the potential superiority ofthe IGA in optimization tasks, warranting further scrutiny and potential deployment in practical scenarios.

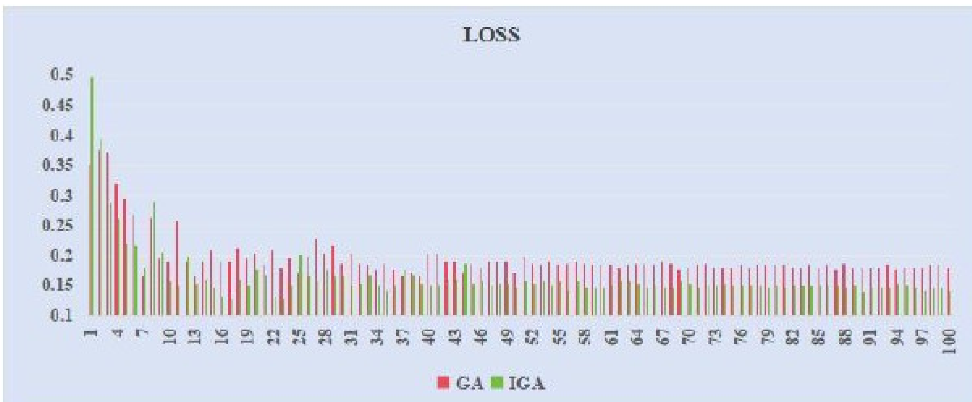

Fig. 4. Loss changes with the number ofiterations

As depicted in Figure 4, the loss values ofboth the GA algorithm and the IGA algorithm are illustrated across a series of iterations. It's miles obtrusive from the graphical illustration that during the initial stages, the loss values for each algorithms stay accelerated, indicating thatthe model's overall performance has butto attain an greatest country. With the progression of iterations, there's a slow reduction within the loss values for both algorithms, suggestive of an enhancement in version performance. But, splendid disparities emerge between the 2 algorithms. GA set of rules exhibits a slow decline inloss values with pronounced fluctuations discovered in later iterations, while the IGA set of rules showcases a quicker discount in loss values, characterised by way of a extra steady trend in later iterations.

Extra especially, the GA algorithm demonstrates a gradual discount in loss values in the course of the early iterations, with massive decreases turning into glaring solely after approximately forty iterations. Though, big fluctuations persist in subsequent stages. Conversely, the IGA set of rules demonstrates elevated loss reduction inside the early iterations, keeping a quite solid trajectory in later iterations, thereby manifesting superior convergence and stability.

In summary, based totally on the fluctuation patterns observed in the loss values, the IGA algorithm emerges because the desired preference, showing superior overall performance and efficacy all through the iterative technique in comparison to the GA set of rules. Its amazing attributes include multiplied convergence quotes and heightened stability, rendering it well-perfect for tackling greater difficult and high-dimensional optimization challenges.

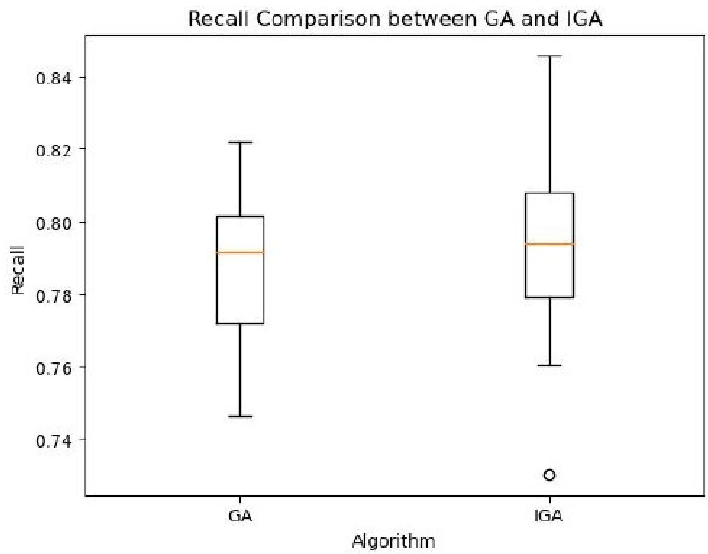

Fig. 5. Comparison curves of Recall

The field plot assessment depicted in Figure 5 truely indicates the superiority of the IGA over the GA concerning the recall price. Particularly, IGA showcases a drastically higher median recall, minimum variability, and a greater said recall bias compared to GA. those observations collectively underscore IGA's improved capability in correctly figuring out pertinent times. The heightened recall exhibited through IGA no longer only signifies its skillability in discerning tremendous cases but also underscores its reliability and performance in functionality assessment tasks.

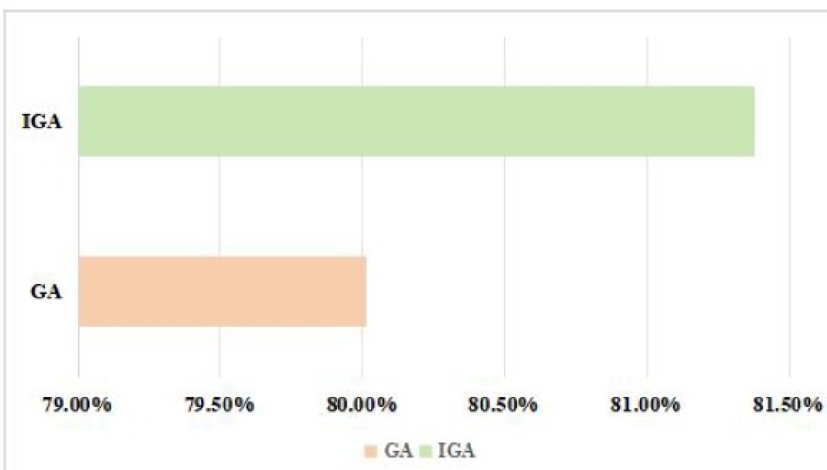

Fig. 6. Comparison curves ofF1 Score

Figure 6 illustrates the precision performance of both the GA and the IGA in the type undertaking. Precision charge, a fundamental metric, delineates the ratio of appropriately predicted superb class samples through the model to the total samples anticipated as fantastic classes.

Commonly, it's first-rate that the IGA algorithm reveals a marginally superior accuracy as comparedto the GAsetofrules. This observation shows thatthe refined GAdisplays more advantageous efficacy on this particular class undertaking. Precision price serves as a pivotal gauge for assessing the version's accuracy in predicting nice instances. Consequently, the IGA algorithm surpasses the GA set ofrules in efficiently predicting tremendous instances.

Even as accuracy serves as a pivotal criterion in comparing version efficacy, it's fundamental to integrate different metrics foraholistic assessment ofversion performance. As a result, even though the IGA algorithm outperforms the GA algorithm in terms ofaccuracy, a complete evaluation ofmodel overall performance necessitates the mixing ofdiverse metrics for a more nuanced evaluation.

5. Conclusion and Discussion

This take a look at proposes an automated category and storage approach for electronic clinical statistics primarily based on an IGA, aiming to deal with the type storage trouble in digital clinical file control. Thru experimental validation, we observed that the IGA has demonstrated promising outcomes in classification storage duties and reveals certain blessings over the conventional GA. mainly, the IGA showcases progressed robustness in terms of convergence velocityand exploration ofthe hunt area, thereby improving class accuracy and performance.

However, this examine encounters numerous boundaries. On the whole, our experiments have been restrained to a small-scale dataset, warranting similarly validation of overall performance in massive-scale sensible software eventualities.Additionally, the proposed IGA requires fine-tuning of certain parameters to achieve optimal performance. Furthermore, our focus was solely on the application of GA in electronic medical record classification storage, neglecting the potential of exploring other optimization algorithms.

In conclusion, this study introduces an automated classification and storage approach for electronic medical records leveraging an IGA, validated through experiments on small-scale datasets. Despite its limitations, we envision promising prospects for the application of IGA in electronic medical record management. Through ongoing refinement and optimization, we aim to deliver more efficient and intelligent solutions for electronic medical record management, thereby advancing medical informatization and enhancing the quality and efficiency of medical services.

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