International Journal for Innovative Engineering and Management Research
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IJIEMR Transactions, online available on 12th Nov 2017. Link
:http://www.ijiemr.org/downloads.php?vol=Volume-06&issue=Issue 11

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Volume 06, ISSUE 11, Pages: 546-555

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International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
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Utilizations of Genetic Algorithms in Medicine : A Review

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***Abstract*:** Medical research data contains a vast amount of information that, in certain situations, cannot be readily or even at all be examined using traditional statistical techniques. Metaheuristic algorithms have been created to provide optimum or nearly optimal solutions to complicated data analysis and decision-making tasks in a reasonable amount of time. These algorithms are inspired by nature. Metaheuristic algorithms have been widely applied in numerous scientific domains due to their potent properties. Nevertheless, doctors who may benefit from using these algorithms to address challenging medical issues are unaware of their application in medicine. Thus, we introduce the genetic algorithm and its uses in medicine in this study. Radiology, radiotherapy, oncology, paediatrics, cardiology, endocrinology, surgery, obstetrics and gynaecology, pulmonology, infectious diseases, orthopaedics, rehabilitation medicine, neurology, pharmacotherapy, and health care management are just a few of the medical specialties where the use of the genetic algorithm has promising applications. This study provides an introduction to the genetic algorithm's uses in illness detection, diagnosis, planning of treatments, pharmacovigilance, prognosis, and health care administration. It also helps doctors imagine potential uses for this metaheuristic technique in their future medical practise.

Keywords: Medicine; Systems; Genetic Algorithm; Optimization; Heuristic approaches.

1 INTRODUCTION

Computers have without a doubt transformed our way of life. Nearly all areas of study, including astronomy, biology, chemistry, physics, mathematics, geography, archaeology, engineering, and social sciences, use them extensively and have profited from them. Many imaging, diagnostic, monitoring, and therapeutic equipment in medicine are powered by electronic chips and computers. Software, which is based on algorithms, manages and controls these devices, which are made up of various hardware components. A well-defined set of guidelines and instructions that specify an order of actions is known as an algorithm. When traditional approaches are unable to provide an accurate answer, metaheuristic methods can solve complicated issues more rapidly or can find a rough solution.

There are several metaheuristic algorithms available for finding an ideal or nearly ideal solution. These include the ant colony (based on the behaviour of ants), the artificial bee colony (based on the behaviour of bees), the Grey Wolf Optimizer (based on the behaviour of grey wolves), the simulated annealing, the river formation dynamics (based on the process of river formation), the artificial immune systems (based on the function of immune systems), and the genetic algorithm (inspired by genetic mechanisms). In various scientific disciplines where it is necessary to solve complicated issues or make the best choices, metaheuristic methods are widely utilised. Although significant progress has been made, the potential of these powerful algorithms to provide answers to the myriad complicated issues that doctors face on a daily basis has not yet been completely realised.We present the genetic algorithm (GA) as one of these metaheuristics in this study and go over some of its medical applications.

The genetic algorithm

A GA is a metaheuristic method, inspired by the laws of genetics, trying to find useful solutions to complex problems. In this method, first some random solutions (individuals) are generated each containing several properties (chromosomes). Based on the laws of genetics, cross-over and mutations occur in chromosomes to produce a second generation of individuals with more diverse properties.

Crossover and mutation are the two most central methods for diversifying individuals. In crossover, two chromosomes are chosen. Then a crossover point along each chromosome is chosen followed by the exchange of the values up to the crossover point between the two chromosomes [Figure 1]. These two newly-generated chromosomes produce new offspring. The process of crossover will be iterated over and over until the desired diversity of individuals (i.e. solutions) is made. The mutation also generates new configurations by applying random changes in different chromosomes.[10] One of the simplest mutation methods has been depicted in Figure 1.

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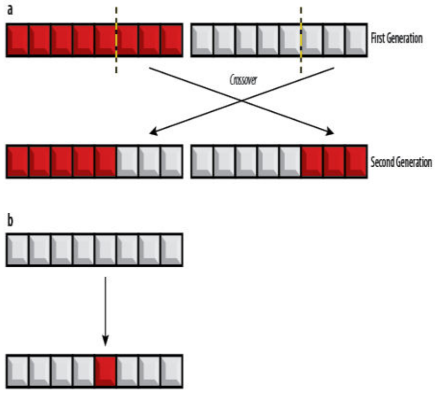

Figure 1: Methods to induce diversity in the population of individuals (candidate solutions). **(a)** During crossover, one part of a chromosome is exchanged by another fragment of another chromosome. **(b)** During mutations, one or more datasets on a chromosome are converted to different ones. These alterations will generate new individuals whose fittest (more optimal solutions) will survive.

2 A BRIEF REVIEW

In a GA, the possibility of reproduction depends on the fitness of individuals. The better chromosomes they have (i.e., those with better characteristics), the more likely they are to be selected for breeding the next generation. There are several selection methods; however, the aim of all is to assign fitness values to individuals based on a fitness function and to select the fittest. Genetic alterations in chromosomes will happen via crossover and mutations to produce another generation. This iterative process will continue until the fittest individual (the optimal solution) is formed or the maximum number of generations is reached.[9,11]

It is worth noting that GAs are different from the derivative-based, optimization algorithms. First of all, GAs search a population of points in the solution space in each iteration while classical derivative-based methods search only a single point. Moreover, GAs select the next population using probabilistic transition rules and random number generators while derivative-based algorithms use deterministic transition rules for selecting the next point in the sequence.[11,12]

In the following, we introduce some of the applications of GAs in a variety of medical disciplines.

Radiology

Imaging techniques in radiology generate a large amount of data that needs to be analyzed and interpreted by radiologists in a relatively short time. Computer-aided detection and diagnosis are rapidly growing interdisciplinary technologies that aim to assist radiologists in faster and more accurate image analysis by detection, segmentation, and classification of normal and pathological patterns found on various imaging modalities. These include X-rays, magnetic resonance imaging (MRI), compute tomography (CT) scan, and ultrasound.[13]

In machine vision, an image of scenery (such as organs of the human body in radiology images) is acquired, processed, and interpreted. The boundaries (shape) and sizes of objects within the images need to be determined to assess the objects in more detail. Therefore, the process of edge detection becomes one of the integral parts of automatic image processing techniques.[14] Several researchers have used the GAs for edge detection of images acquired using different imaging modalities including MRI, CT, and ultrasound.[14-16]

Screening mammography is the gold standard for detection of breast cancer; however, due to its failure rate,[17,18] researchers have tried to apply computational tools to improve the sensitivity of the system. In fact, the majority of the applications of GAs in radiology were performed on breast cancer screening primarily using mammography.

Karnan and Thangavel[19] applied the GA to detect microcalcifications in mammograms suggesting of breast cancer. In their method, after enhancement and normalization of the mammograms, the border of breast and the nipple position was detected by the GA. Using the border and the nipple position of the right and left breasts as a reference, the mammogram images were aligned and subtracted from each other to find the asymmetry image suggestive of breast cancer. The Az value, which is the area under the receiver operating characteristic (ROC) curve, has been used as a useful measure for assessing the diagnostic performance of a system.[20] The Az value for their proposed algorithm was about 0.9.[19]

In another study, Pereira et al,[21] applied a set of computational tools for mammogram segmentation to improve the detection of breast cancer. An algorithm was first designed to eliminate artifacts followed by denoising and image enhancement. Consecutively, combining wavelet analysis and the GA allowed detection and segmentation of suspicious areas with 95% sensitivity. GAs have also been successfully used for classification and detection of clustered microcalcifications in digital mammograms.[22-24]

In machine learning, feature selection is the process of selecting a subset of relevant features to construct a model by removing variables with little or no analytical value. Feature selection is important since choosing irrelevant features would increase the time, cost, and complexity of computation and reduce the accuracy of the model.[25] Besides, reducing the number of features would avoid the problem of over-fitting, reduce the chance of failure upon missing data, and allow for a better explanation and generalization of the model.[26]

GAs have been applied for feature selection in studies aiming to identify a region of interest in mammograms as normal or containing a mass,[27] and to differentiate benign and malignant breast tumors in ultrasound images.[25]

de Carvalho Filho et al,[28] developed a GA for automatic detection and classification of solitary lung nodules. The designed algorithm could detect lung nodules with about 86% sensitivity, 98% specificity, and 98% accuracy.

Image registration or fusion is the process of optimal aligning of two or more images into one coordinate system. Precise integration of images becomes crucial when valuable information is embedded within several images acquired under different conditions (viewpoint, sensor, or time).[29] GAs have successfully been used to align MRI and CT scan images in several studies.[30,31] In another study, positron emission tomography (PET) images were fused with MRI images by a GA to generate colored breast cancer images.[32]

Precise tumor staging is an important part of designing a treatment plan. Accurate tumor size and volume determination using non-invasive imaging studies becomes essential for tumor staging. Zhou et al,[33] developed a system for extraction of tongue carcinoma from head and neck MRIs. A GA was applied for segmentation of images followed by an artificial neural network (ANN)-based symmetry-detection algorithm to reduce the number of false positive results. This approach was able to extract tongue carcinoma from an MRI with high accuracy and minimal user-dependency.

Oncology

Screening tests offer a valuable opportunity for early cancer detection, which if followed by proper treatment could improve the survival rate of patients.

To develop a non-invasive technique for cervical cancer detection, Duraipandian et al,[34] acquired Raman spectra from the cervical area via colposcopy. The biomolecular information generated via the Raman spectroscopy was analyzed by a GA-partial least square-discriminant analysis system to differentiate between a normal and dysplastic cervix. Partial least square (PLS) is a statistical method aiming to find a linear regression model between a dependent variable and some predictor variables.[35] This system was able to differentiate dysplasia from a normal cervix with 72% sensitivity and 90% specificity.[34]

The advent of DNA microarrays has paved the way for massive gene expression profiling that could revolutionize the field of molecular diagnostics and prognosis. However, generation of large sets of data poses statistical and analytical challenges necessitating the need to find key predictive genes.[36] Due to the inherent capability of GAs to search and find the optimal solution among large and complex possible solutions with multiple simultaneous interactions, they have been applied to analyze microarray data from several cancer cell lines.[36] Dolled-Filhart et al,[37] generated microarray data by staining breast cancer tissues with several antibodies specific for various markers to find a minimum set of biomarkers with maximum classification and prognostication values in breast cancer patients. The data analyzed using GAs showed that three markers with available antibodies could define a population of patients with more than a 95% five-year survival rate.

Tan et al,[38] conducted a study to investigate the relationship between soil trace elements and cervical cancer mortality in China. A combination of GA and PLS was used to choose five out of 25 trace elements. Then a least square support vector machine (LSSVM) model was developed. LSSVM is a method used in machine learning to infer a function from or find a pattern in training data.[39] The results showed that a combination of GA-PLS and LSSVM could predict the mortality of cervical cancer based on trace elements.[38]

One of the important and informative factors influencing the choice of an appropriate therapeutic approach for cancer patients is determination of the disease prognosis. In a retrospective study on more than 200 patients, Bozcuk et al,[40] compared the performance of four different data mining methods to determine the outcome of cancer patients not being in terminal stages after hospitalization. In comparison to other methods, GA selected the least number of explanatory variables (lactate dehydrogenase and the reason for admission) to predict the outcome of patients.

Cardiology

GAs have been used in different fields of cardiovascular medicine. Atherosclerotic plaques are hallmarks of most myocardial infarctions and strokes. Determination of plaque mechanical properties such as elasticity would enable physicians to locate better and map vulnerable or unstable plaques. Khalil et al,[41] used a system involving GAs for parameter estimation necessary for accurate elasticity quantification to determine tissue elasticity. This system is superior to gradient-based methods used for parameter estimation of the inefficiency of gradient-based techniques for inhomogeneous solution spaces containing several local minima and requirement for substantial computational time limits their application.[41]

The field of biomarker discovery and clinical proteomics is rapidly growing in medical diagnosis, prognosis, and disease follow-up. Advanced technologies such as mass spectrometry can generate readouts of thousands of proteins from patient samples; however, the cost and complexity of such techniques on the one hand and computational and statistical methods for analysis, on the other hand, necessitates the selection of a few, relevant markers for clinical assay development. Zhou et al,[42] employed an improved version of the GA supported by a recursive local floating enhancement technique to predict the risk of a major adverse cardiac event (MACE). This technique was able to select a panel of seven proteins including myeloperoxidase to predict the risk of MACE with 77% accuracy, which outperformed over several current methods.

Logistic regression models have been frequently used in diagnosing diseases. Due to its outstanding performance, a GA has been used to select the best variables for a logistic regression system aiming to model the presence of myocardial infarction in patients with chest pain. The GA-based method was superior in variable selection to other traditional methods.[26]

One of the key elements in the automatic interpretation of the electrocardiogram (ECG) is the detection of QRS complexes that would allow assessment of heart rate variability and other relevant diagnostic parameters. Tu et al,[43] introduced a simple and effective GA to detect QRS complexes. Then, p-waves and f-waves, which happen in normal ECG and after atrial fibrillation, respectively, were successfully extracted from patient databases. Such algorithms could allow comprehensive research into ECG details.

Endocrinology

Hypoglycemia is the most common complication of insulin therapy in patients with type 1 diabetes mellitus (T1DM). Hypoglycemia can induce alterations in the patterns of electroencephalograms (EEGs). Nguyen et al,[44] combined ANNs, GAs, and Levenberg-Marquardt (LM) training techniques to detect hypoglycemia based on EEG signals. ANN was used to model the relationship between blood glucose and EEG signals. For training ANN, the global search ability of GA and the local search capability of LM were combined. Data from four EEG parameters derived from two EEG channels were used by the analyzing system to detect hypoglycemia with 75% sensitivity and 60% specificity. In another paper, a GA-based multiple regression with fuzzy inference system was developed to detect non-invasive episodes of nocturnal hypoglycemia in children with T1DM. Using heart rate and corrected QT interval, hypoglycemia was detected with a sensitivity of 75% and specificity of over 50%.[45]

Obstetrics and gynecology

The differentiation between normal and prolonged delivery allows obstetricians to determine the optimal timing for interventions, if necessary, during childbirth. One of the parameters that can help to forecast the delivery time and segregate normal versus prolonged labor is the time to reach full cervical dilation. Hoh et al,[46] applied a three-parameter logistic model using GA or the Newtone-Raphson (NR) method to predict the time to reach full cervical dilation. The GA-based algorithm outperformed the NR method by more accurately predicting the time to full cervical dilation.

A Pap smear is a cytology test for detection of precancerous and cancerous cervical changes. In this method, 20 features of cells are assessed to describe them as normal or abnormal or, more specifically, categorize them into seven classes. Marinakis et al,[47] generated a hybrid model that took advantage of the feature-selection capability of GAs to reduce the complexity of features necessary for a nearest neighbor algorithm for classification of Pap smear results. The new method outperformed several other previously used approaches by accurately classifying the Pap smear results.

GAs have also been applied in prenatal diagnosis. One of the fetal features that can complicate delivery is fetal macrosomia. In an attempt to differentiate the large-for-gestational-age (LGA) from the appropriate-for-gestational-age (AGA) infants, amniotic fluid from the second trimester was evaluated by capillary electrophoresis. Bayesian statistics was applied for data analysis. A GA was used to select the suitable wavelets (variables) of the electropherogram to minimize the computation time required for the Bayesian computation. This system was able to differentiate LGA from AGA using only two wavelets, one of albumin and the other of a negatively-charged unknown small molecule with 100% sensitivity and 98% specificity.[48]

The prediction of fetal weight before delivery can reduce the potential problems associated with low-birth-weight infants. Yu et al,[49] introduced fuzzy logic into the support vector regression (FSVR) to estimate the fetal weight. GAs were used to generate an evolutionary FSVR to select the optimal features for the FSVR system. This outperformed a back-propagation neural network by achieving the lowest mean absolute percent error (6.6%) and the highest correlation coefficient (0.902) between the estimated and the actual fetal birth weight.

Pediatrics

Cardiotocography is a cheap and non-invasive technique to assess the fetal heart rate and uterine contractions to determine fetal well-being. Ocak[50] applied a GA to select the optimal features of cardiotocogram recordings for a support vector machine (SVM) classifier. The results showed that the new system classified fetal health status as normal or abnormal with 99.3% and 100% accuracy, which was superior to an ANN algorithm designed for the same purpose.

Autism is a neurodevelopmental disease that appears in early childhood and is characterized by impaired social functioning and verbal and non-verbal communications and repetitive behavior. To recognize autism based on the microarray gene expression data, Latkowski and Osowski[51] used GAs to select the most relevant genes associated with the disease. Frequently selected genes include RMI1, NRIP1, TOP1, ZFHX3, CEP350, NFYA, PSENEN, ANP32A, SEMA4C, and SP1. These genes

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provided an input for an ensemble of classifiers including SVM and random forest classifiers. The introduced system recognized autism with 96% sensitivity and 83% specificity.[51]

Acute lymphoblastic leukemia (ALL) is the most common type of leukemia in children and has many subtypes. Analysis of gene expression data derived from tumor cells can help classifying cancers. Due to the enormous size of information generated from microarray gene expression profiling, Lin et al,[52] used a GA to select the most relevant genes needed for ALL classification. Silhouette statistics was applied as a discriminant function to differentiate between six ALL subtypes. The proposed technique reached a 100% classification accuracy and used fewer discriminating genes compared to other methods.

Aneuploidy is a condition where one or a few chromosomes in the nucleus of a cell are above or below the normal chromosomal number of a species. Conventional chromosomal studies on amniocentesis samples are performed for definite diagnosis of fetal aneuploidy yet the rather long required time for these techniques necessitates the development of faster diagnostic tests. To this end, the proteomic profile of the amniotic fluid specimens was identified via mass spectrometry and the generated data was assessed by a GA. The proposed method could detect aneuploidy with 100% sensitivity, 72%–96% specificity, 11%–50% positive predictive value and 100% negative predictive value.[53]

Surgery

ANNs are powerful mathematical algorithms capable of predicting the behavior of systems. Due to the predictive value of ANNs, a GA-based ANN (GANN) was developed to predict the outcomes after surgery for patients with non-small cell lung cancer (NSCLC). The GA was applied to help optimization not to fall into local minima. The GANN model could predict the outcome of NSCLC patients more accurately and significantly better than logistic regression. Besides, the inclusion of tumor size in calculations significantly improved prediction outcomes.[54]

As populations age, the number of geriatric patients needing cardiac surgeries increases. Due to the high prevalence of comorbid conditions in elderly, proper prognostication of postoperative morbidity and mortality would be informative, precluding overestimation of risk and denial of surgery for patients deserving it, which could happen with some prediction models. Applying a GA, Lee et al,[55] showed that a short length of stay after cardiac surgery was correlated with younger age, no preoperative use of beta blockers, shorter cross-clamp time, and absence of congestive heart failure.

Pulmonology

In pulmonology, auscultation is the most common diagnostic method that can differentiate lung diseases and guide the diagnostic approach toward more specific techniques. To automate lung sound diagnosis, a hybrid GANN was designed. The GA was applied to optimize the ANN training parameters and reduce the computation time. The new system could classify the lung sounds into normal, wheeze, and crackle.[56]

Assessment of the partial pressure of carbon dioxide in the arterial blood (PaCO2) is important in the management of critically ill patients. To avoid difficulties associated with arterial blood sampling, non-invasive methods for predicting PaCO2 such as assessment of exhaled carbon dioxide at end-expiration (PetCO2) could be applied in normal individuals; however, their use in sicker persons might be biased and less helpful. Engoren et al,[57] designed a GA to predict the PaCO2 using 11 variables from capnography of non-intubated patients in the emergency department. The proposed system could improve the precision and bias of PaCO2 prediction.

Infectious diseases

Tuberculosis is a possible lethal infectious disease not only in developing countries but also in developed nations after the emergence of human immunodeficiency virus (HIV). To predict the diagnosis (tuberculosis vs. non-tuberculosis patients), 38 parameters composed of examination parameters and laboratory data were used to design an ANN trained by a GA. The classification accuracy of the system was about 95%, which was higher than the results obtained by other algorithms.[58]

Highly active antiretroviral therapy (HAART), an integral part of the treatment modalities against HIV, is composed of a combination of several antiretroviral medications aiming to decrease the replication of the virus. Since long-term HAART treatment needs patient compliance and might be associated with some side effects, structured treatment interruption has been proposed to reduce not only side effects, but also the selection pressure on the virus that could lead to the emergence of resistant particles. Therefore, Castiglione et al,[59] devised a GA-based system to choose the best HAART treatment schedule to control HIV and help the immune system to reconstitute. A virtual model of the immune system was used to assess the effects of anti-HIV drugs on virtual patients.[59,60] The new structured interruption schedule could achieve therapeutic results and protection against an opportunistic infection comparable to a full-length treatment.[61]

Radiotherapy

Intensity modulated radiotherapy (IMRT) was developed to transfer an accurate dose of radiation to a target such as the brain, prostate, or head and neck. Planning IMRT involves selection of 5–10 angles for wavelet projection and determining the radiation dose. The application of GA could improve the selection of gantry angles in a reasonable time frame.[62] Similar GA-based irradiation planning has been applied for patients with other types of cancer including pancreatic,[63] rhabdomyosarcoma, and brain tumors.[64] GAs have also been successfully used to optimize the design of stereotactic radiosurgery, and radiotherapy treatment plans.[65]

Rehabilitation medicine

As the need for physical rehabilitation increases, novel treatment equipment and techniques have to be developed and tested. Refinement of these new methods needs changing various parameters and testing of the resultant techniques on individuals, which is time-consuming and costly. Development of musculoskeletal models enables computer simulation of movements to assess the effect of new modifications on the efficiency of training. Pei et al,[66] developed a robotic technique for physiotherapy of the lower limb. A GA was applied to generate custom-made treatment plans for each patient.

In another paper, a therapeutic robot was designed for lower limb exercise. The system that consisted of an ANN and a GA was capable of learning the actions of a physiotherapist for each patient and mimicked its behavior in the absence of a therapist.[67]

Orthopedics

Biomedical engineering has offered great solutions to the field of orthopedic surgery. Total hip arthroplasty (THA) has improved the management of various disabling hip joint diseases. Yet, failure of the femoral stem of a THA can compromise the success of treatment. Ishida et al,[68] reported the use of a GA in designing an optimized geometry of the femoral stem component. GAs have also been exploited to select the best design of tibial locking screws to reduce the probability of screw breakage or loosening.[69] In another report, a combination of ANNs and GAs was applied to design spinal pedicle screws used for fixation of spinal fractures. The hybrid algorithm was able to design screws with a higher fatigue life and ideal pullout and bending characteristics.[70]

Scoliosis is a three-dimensional deformity of spinal axis curves. The progression of the disease, which only happens in a small percentage of patients, is monitored by serial X-rays over time. Since frequent exposure to X-rays might increase the chance of cancer, it is desirable to assess the disease development using harmless methods. Jaremko et al,[71] developed a GA-based ANN algorithm to estimate the angle of spinal axis deformity from indices of trunk surface deformity. The hybrid system was able to determine the angle deformity within 5% accuracy in more than two third of patients.

Neurology

Multiple sclerosis (MS) is a debilitating inflammatory disease of the neural system characterized by the formation of white matter scars otherwise known as plaques. Computer-assisted diagnosis has been applied for detection of pathologic features in these patients. In one study, a GA was developed to detect the MS lesions of brain MRIs. The similarity index of lesions determined by the GA and by a radiologist was 87%.[72]

The EEG is a useful diagnostic method to detect the abnormal brain electrical discharges occurring during a seizure. To design an automated system for detection of abnormal EEG signals, several learning algorithms (LM, Quickprop, Delta-bar delta, and Momentum and Conjugate gradient) were used to train an ANN for EEG-based classification of epileptic versus healthy individuals. A GA was used to find the optimal parameters for and architecture of the ANN. The results demonstrated that the LM method combined with the GA was the best algorithm for training the ANN, which reached a general success of 96.5% in its performance.[73]

Several reports have suggested that mitochondrial dysfunction plays an important role in Parkinson's disease. Since mitochondrial genetics has its idiosyncrasies, a simple comparison of mitochondrial mutations between healthy and disease conditions might not be so informative. Therefore, Smigrodzki et al,[74] devised a GA to detect biologically important patterns of mitochondrial mutations in Parkinson's patients. The proposed system was able to diagnose Parkinson's disease with 100% accuracy based on mutational patterns in mitochondrial DNA.

Pharmacotherapy

Pharmacovigilance, the study of safety and adverse effects of drugs, is not only an integral part of currently-used drug assessment; it is also a crucial element in the evaluation of novel investigational medicines. The clinical judgment of a pharmacotherapist to attribute an observed adverse effect to a drug is valuable yet implicit while algorithms can make a less arbitrary and more objective evaluation. Koh et al,[75] developed a GA-based quantitative system for the evaluation of adverse drug reactions. The new scoring system was able to determine a probability of the causality of an adverse drug reaction to a suspected drug with about 84% sensitivity and 71% specificity.

Tacrolimus is an immunosuppressive agent used to prevent rejection after organ transplantation. The drug has highly variable pharmacokinetics and a narrow therapeutic window making its blood level control an essential and difficult task. In an attempt to predict the blood concentration of tacrolimus in liver-transplanted patients, an ANN algorithm was developed. A GA was used to choose the best set of clinically significant candidate variables. For validation, predicted results were compared to observed

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figures. The ANN was able to predict the blood level of tacrolimus, with 84% of data sets being within a clinically acceptable range of 3 ng/ml of the observed data.[76]

Studies have shown that poor pharmacokinetics and lack of efficiency account for more than 50% of failures in the process of drug development. The traditional assessment of the efficacy and pharmacokinetics of novel investigational agents in animal models is a costly and time-consuming process. Therefore, computational methods have evolved to generate quantitative structure-pharmacokinetic relationship (QSPKR) models for rapid in silico screening of novel potential drugs.

Zandkarimi et al,[77] applied a GA to select the most suitable characteristics out of more than 1480 descriptors of alkaloid drugs. These sets of characteristics were then extracted from known drugs for training an ANN to generate QSPKR prediction models. The new system was able to predict the volume of distribution, clearance, and plasma protein binding of alkaloid drugs with an acceptable efficiency.

Health care management

Proper management of monetary resources and personnel is an integral part of health systems all over the world. One of the important elements of hospital management which can improve patient servicing, satisfaction, and cost-effectiveness ratios is efficient scheduling of patients admission. A mathematical model was developed and optimized using a GA to improve the patient scheduling in an ophthalmology hospital. The new algorithm was superior to the traditional "first come, first serve" model in that it shortened the waiting list, lowered the vacancy rate of hospital beds, reduceed the preoperative waiting time for patients, and increased the number of patients discharged from the hospital.[78] Another report showed that a combination of GA and particle swarm optimization, another powerful metaheuristic algorithm, was able to improve patient scheduling, reduce time wastage, and increase patient satisfaction.[79]

In clinical laboratories, regular rotation of staff based on their skills through different facilities is fundamental for maintaining job skills and competence. GAs have been applied to improve staff rotation scheduling in a clinical laboratory. In one report, the GA-based software was capable of planning the rotation of staff effectively, ensuring maintenance of techniques and skills, saving time and the cost necessary for the scheduling process, and it was associated with the satisfaction of responsible supervisory personnel.[80]

3 CONCLUSION

We introduced GAs and some of its uses in diverse areas of medicine in this study. Although though GAs and several other metaheuristics were inspired by biology, scientists in other disciplines of study are more familiar with these techniques and routinely employ them to tackle challenging issues. Because medicine is inherently complicated, optimization techniques might be very helpful to doctors and medical researchers. This predicament results from a lack of effective communication between computer scientists and physicians on the one hand, and from the medical professionals' lack of familiarity with sophisticated mathematical formulae on the other. Hence, increasing communication and understanding between doctors, computer scientists, and engineers might be the solution. This could be done by hosting joint journal clubs or by attending doctors' ground rounds and case report presentations. Also, the development of multidisciplinary curricula and the effective participation of engineering researchers in hospitals and health care settings may provide fresh approaches to medical issues as well as fresh perspectives for non-medical researchers.

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