

Received April 8, 2020, accepted April 16, 2020, date of publication April 28, 2020, date of current version May 15, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2991016

Disease Classification in Health Care Systems With Game Theory Approach

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ABSTRACT There are numerous cases in real life when we come across problems involving the optimization of multiple objectives simultaneously. One of the complexities of solving such problems is that often one or more objectives are usually conflicting under given conditions. In this study, the benefits of relying on a deployed Clinical Decision Support System (CDSS) concerning the overall reputation of a health facility has been studied. The analysis is performed in terms of a co-operative Bayesian game-theoretic model. The game is played between two players of which the first player is a patient who needs quick and accurate medical attention and the second player is the hospital administration that relies on medical experts as well as integrated multi-objective clinical data classification systems for decision-making. The proposed model “MEAF” - Multi-objective Evolutionary Algorithm using Fuzzy Genetics attempts to address accuracy and interpretability simultaneously using Evolutionary Algorithms (EAs). This model enables a H_{CDSS} to detect a disease accurately by using the available resources efficiently. The results of our simulation show that H_{CDSS} produces better and accurate results in detecting disease with efficient resource utilization along with the reduced computational cost. This approach has also produced a better response for both players based on Bayesian Nash Equilibrium. Finally, the proposed model has been tested for accuracy, efficient resource utilization, and computationally cost-effective solution.


INDEX TERMS Multi-objective optimization, evolutionary algorithms, game theory, Bayesian models, Nash Equilibrium.

I. INTRODUCTION

Various knowledge base techniques have been introduced in the medical data mining domain to support accurate, efficient and computationally efficient decision-making for health care improvement [1]. CDSS is being used by clinicians to diagnose various diseases instead of conventional statistical systems. Keeping in view the evolving nature of multi-objective optimization problems especially in medical sciences, one of the recent solutions to solving such problems is the evolutionary algorithms. Evolutionary algorithms base their outcome on Pareto Solution set, which has been further defined in the subsequent section of this paper. The significance of current research aims to contribute both in academia as well as industry to enhance their understanding of this relatively less explored domain of research. Academia contribution entails a novel model that can simultaneously optimize the correctness and justification of decision inferred by a genetic fuzzy optimization approach. The industrial

contribution will give medical doctors an assistive model that can help in improved medical health care by predicting an earlier diagnosis of the disease that allows the provision of best practices and high-quality care to the patient, which is the ultimate goal of healthcare. Effective decision-making in healthcare will minimize errors by improving accuracy, interpretability and reducing the computational cost. Some of these errors include prescription errors, adverse drug events, and decisions regarding the prognosis of any disease in a patient. The expected outcome of this research will benefit practicing doctors and ER facilities of hospitals to predict the intensity and nature of the disease. The model will also help the doctors of remote areas where the specialized medical facilities are not available. This will grossly improve the health quality of common masses by assisting the doctors in making correct medical decisions through technological invocation. Further, the model can be evaluated by commissioning it in a depleted environment like Orion Health, Medispan, etc.

Keeping in view the nature and significance of medical domain, evolutionary algorithms are the better choice

The associate editor coordinating the review of this manuscript and approving it for publication was Shangce Gao .

to evolve solutions out of conflicting objectives. Differential Evolution and Genetic Algorithms are two well-known EAs that can be applied to handle multi-objective problems accurately. Genetic Algorithms are applied using biological operators such as mutation, selection, and crossover. The ability of EAs to perform well in numerous multi-objective optimization problems makes them a good choice for use.

Game theory is the study of optimization problems [2]. Multi-objective Algorithms for Evolutionary Game Theory (MOAEGT) have been designed on the notion of Evolutionary Game Theory (EGT) and EAs. Game-theoretic models are based on strategic interactions between two players containing set rules and outcomes [3]. These algorithms syndicate optimality and stability for real-time multi-objective problems. Stability, Optimality, and Meta-heuristics are some of the features of MOAEGT. In addition to this, each individual tries to maximize the corresponding pay-off [4]. While solving such problems, there is a need to list down all acceptable solutions and then choose the optimal solution. An acceptable set of solutions for the multi-objective problem is known as the Pareto Curve. This Pareto Curve forms the solution space of the corresponding multi-objective optimization problem. In this paper, we will describe our proposed model (MEAF) using game theory. Some of the methods to solve multi-objective problems cover the weighted sum method [5], multilevel programming, goal programming, and evolutionary algorithms.

Motivation behind this research is to expedite the well-known accuracy-interpretability trade-off problem in the clinical domain. This will help the earlier prognosis of the disease and will not only help common masses but will allow the government institution to spend less on health care. Furthermore, health insurance companies will easily make out the outlier that will save a lot of finances. Above all, the earlier and correct diagnosis will grossly improve the overall health conditions of a society.

The major research challenge of the proposed research is to handle three conflicting objectives of CDSS that are accuracy, interpretability and computational cost. Accuracy demands more number of rules that increase the computational cost and reduces the interpretability of the decision. MEAF addresses these issues by optimizing the rule set through a genetic algorithm and gaining accuracy through fuzzy inference and evolve a trade-off between conflicting objectives. Furthermore, clinical data has huge volumes and is heterogeneous in nature. Its handling and pre-processing is another major challenge.

The flow of the paper is organized with the intent to establish readers' further clarity about evolutionary algorithms in the background section. Related work introduces to the relevant and current research models in various domains, covering their methodology, strengths, and weaknesses. Section IV is dedicated to describe detailed conceptual thought of proposed research in which proposed model MEAF involving game theory and its evaluations are presented to establish statistical beliefs. Section V presents the performance evaluation

and results followed by section VI that covers the discussion on the generated results. Finally, section VII covers the conclusion and future work.

A. CONTRIBUTIONS

In this proposed work, an attempt has been made to address disease prediction efficiently and cost-effectively using resources of the Hospital Clinical Decision Support System (H_{CDSS}). Our work applies a Bayesian game-theoretic approach to model the strategies of players. It is important to mention here that our model generates the corresponding Nash Equilibrium solution for these strategies to meet optimal accuracy and interpretability. The proposed model applies an evolutionary algorithm that works iteratively to traverse records of patients for given features/attributes. The major contributions of our work are summarized below:

- 1) The usage of H_{CDSS} as the main source based on the Bayesian game-theoretic model for iterating patient records to perform disease prediction. To the best of our understanding, this model is unique in its approach to predict disease by efficient resource utilization of respective H_{CDSS} .
- 2) Presentation of resource-intelligent model that is iterative in nature, which uses type space as 'healthy' or 'sick' in pairs before reaching to stable strategy. This notion makes it more realistic to predict disease by enhancing the ability of Hospital Administration (HA) to make correct decisions.
- 3) Performance evaluation of our proposed study is based on various parameters that influence the strategies of both players. Performance parameters consist of the true positive rate analysis, cost of iteration for patient records, cost of penalty & total resource distribution.

II. BACKGROUND

Multi-objective optimization problems are found everywhere. In most of the cases, there are two, three or more conflicting parameters that are to be optimized simultaneously. Evolutionary Algorithms are one of the ways to solve the optimal solution from a given solution space. EA may not be able to devise a solution by optimizing all conflicting parameters instead it will offer the optimized solution based on those conflicting objectives. In multi-objective optimization problems, the utopia point states the ideal solution for the conflicting objectives that are not possible to be achieved. In the case of multi-objective problems, the resultant outcome should satisfy all objectives at the same time. Therefore, in such cases, there is usually more than one solution that satisfies each objective, which forms Pareto Optimal Solution.

Researchers are working in this domain with eager to evolve the best possible solutions. The research proposed in [6] is named as Moth-Flame Optimization (MFO) meta-heuristic algorithm. The basic purpose of this research is to address the Web Service Composition (WSC) problem in a cloud environment to improve QoS criteria. Some of the QoS

criteria that are improved by this proposed method include cost, time, reliability and availability. This novel approach outperforms other state-of-the-art algorithms such as Particle Swarm Optimization (PSO), ant colony optimization and Genetic Algorithm (GA). Future directions for this approach include the development of a linear programming strategy to make it more practical and effective.

The research study conducted in [7] is an extensive survey and taxonomy of the bio-inspired Virtual-Machine Placement (VMP) algorithms. The placement of VMs is considered an NP-hard problem. The basic purpose of this study is to present a deep insight through a literature review of various VMP approaches and highlight their different aspects. Some of the parameters of consideration for VM placement include minimizing energy consumption, resource wastage, and service level agreement violations while increasing some parameters including performance and QoS of cloud infrastructure. This study lists various benefits that are achieved by using bio-inspired optimization algorithms. However, future improvement considerations may include VM placement and migration in the cloud environment, security, and more accurate workload prediction.

To address the web service composition problem in a cloud computing environment, a new method is proposed in [8]. This new method is based on the cuckoo search algorithm called 'CSA-WSC'. The experimental results of this approach are compared with other approaches including the genetic particle swarm algorithm (PSO) and Search Skyline Network (GS-S-Net), which demonstrate that cost and response time is reduced to 7% and 6% respectively. The availability and reliability are also increased up to 5.5% and 7.25% respectively. Some of the future works for this algorithm include the development of a linear programming strategy so that it becomes more effective and practical.

To address the NP-hard optimization problem in a distributed cloud environment, a new research study is proposed in [9]. This new study is based on the linear programming approach to solve the web service composition problem known as LP-WSC. The fundamental aim of this approach is to improve the quality of service criteria. Evaluation of this approach with other approaches reveals that this new approach reduces the cost considerably as well as increases availability and reliability. However, there is still a need to develop this new scheme using migration algorithms.

The research study presented in [10] is a thorough review of recent researches that is conducted to place virtual machines (VMs) in the cloud environment. This exceptional review has enlightened key parameters and schemes that are used to place VMs into physical machines (PMs) in a live depleted environment.

A. PARETO OPTIMAL SOLUTIONS

The set of all acceptable solutions to any multi-objective problems is known as Pareto Curve or Pareto Space. There can be a situation in which the solution cannot be achieved without degrading the value of one of the objectives. Such

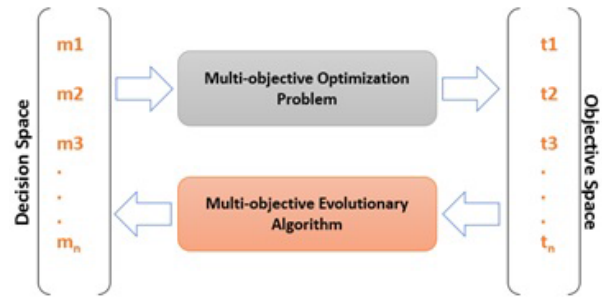


FIGURE 1. Evolutionary Algorithm Workflow.

solutions are known as Pareto Optimal. All Pareto Optimal solutions formulate Pareto Front. In [11] an improved game theory model, coupled with an adaptive differential evolution algorithm, is proposed to generate the Pareto front of the multi-objective trajectory optimization problem.

B. MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS

In many real-world problems, we have to make decisions by keeping in view more than one objective. In short, there are more than one solution to our respective problem but we are only interested in the most optimal solution. Multi-objective evolutionary algorithms may not find the exact outcome but in many cases, we need to find an optimal solution, which serves our purpose. For a given multi-objective problem, Figure 1 shows the optimization workflow of evolutionary algorithms. Multi-objective evolutionary algorithm where $m_1, m_2, m_3, \dots, m_n$ show the decision space and $t_1, t_2, t_3, \dots, t_n$ expresses the objective space.

Significant advantages of multi-objective evolutionary algorithms are as under:

- 1) These algorithms iterate to search for complete Pareto Front in place of a single optimized solution.
- 2) EAs work on problems involving multi-objective without knowing the area of the problem.
- 3) EAs do not assume anything about Pareto Curve.
- 4) EAs attempt to generate an approximated set by incurring a reasonable computational cost.

Multi-objective evolutionary algorithms are the widely researched area know a day and the research presented in [12] is based on a self-learning fuzzy method that is aimed at dynamic resource allocation in a cloud environment for Multiplayer Online Games (MMOG). The development of an improved poison distribution attempts to predict future requests from a historical repository. This approach attempts to deal with multiple objectives of response time and cost when new players arrive. The dynamic computation of resources in each interval is based on workload and player's Service Level Agreement (SLA). The experimental results and evaluations of this approach with other similar methods have shown the superiority of proposed work over others in terms of cost and response time. However, the categorization of workloads and predicting the respective model for each

workload is not addressed and can be considered for future works.

The research study proposed in [13] is based on a hybrid dynamic resource provisioning scheme in a cloud environment for multi-tier applications known as Fuzzy Analytical Hierarchy Process (FAHP). It is called hybrid because it is based on the autonomic computing method along with the concept of the fuzzy analytical hierarchy method. The prediction model is based on Support Vector Regression (SVR). This scheme attempts to present automatic resource provisioning to multi-tier applications as soon as the new user connects. The proposed approach is tested for response time, cost and number of virtual machines. The results of evaluations reveal that this approach provides better control over SLA violations and meets the QoS requirements of the user. However, the proposed system is not tested in a real cloud environment, which suggests that future work should cover this matter too.

To solve the problem of QoS and load balancing in cloud computing, a new adaptive approach is proposed in [14]. The concept of this approach is a combination of Best-Worst Multi-objective decision-makers (BMW) and a ranking scheme called VIKOR. This approach is evaluated and experimental results are compared with other approaches including Quick response, Min Connections, Low-Cost Rate & Minimum Connection (LRTM) and Secure Socket Layer (SSL). The results show that this new adaptive method has achieved better value for user response time and VM usage. However, this method can be extended in the future by implementing some other decision-making techniques including Fuzzy TOPSIS and Extended VIKOR.

The work presented in [15] is a solution to video coding demands of high-quality video coding applications. The new method called high-efficiency video coding (HEVC) meets the demands of modern video coding as compared to existing video standards e.g. MPEG-2, MPEG-4, and H.264. The proposed method uses varying sizes of coding units (CUs), prediction units (PUs), and transform units (TUs). The basic concept of the HEVC standard is its improved Intra-prediction algorithm, which reduces the computational load. When compared with other video coding schemes, HEVC has shown efficient results in terms of reducing encoding time. This scheme needs to be modified in the future to enhance the acceleration of the encoding process along with hardware implementation of Intra-prediction mode.

Evolutionary algorithms work on decision space to produce the Pareto Front via biological operators. In the upcoming section, the algorithm used in the proposed model MEAF is explained. Algorithm 1 lists the iterations that our proposed approach MEAF performs. In the EA case, the initial generation of decision space is done on a random basis. The operators used by EA are crossover and mutation. These operators are used to generate new offspring from the given original population. The newly generated offspring forms the solution(s). After this stage, the objective space variables are used to evaluate the solution set.

Algorithm 1 Enhanced Non-Dominated Sorting GA

```

1:  $Pop_o = \text{Initialize Population}()$ ;
2:  $Ref_s = \text{Generate Reference Spot}()$ ;
3:  $Enh_o = \phi \% |Enh_o| = |Ref_s|$ 
4:  $\mu_o = \% |\mu_o| = |Enh_o|$ 
5:  $[Enh_{t+1} + \mu_{t+1}] = \text{UpdateEnhanced}(Ref_s, Pop_o, Enh_o, \mu_o)$ 
6: do
7:    $s_t = \phi, i = 1, p = 0.5$ 
8:    $Q_t = \phi$ 
9:    $S_p = \text{size}(Pop_t)$ 
10:   $S_E = \text{size}(Enh_t)$ 
11:   $i = 1$ 
12:  do
13:     $r_1 = \text{rand}(1, S_{Pop})$ 
14:     $r_2 = \text{rand}(1, S_{Pop}), r_1 \neq r_2$ 
15:     $r_3 = \text{rand}(1, S_{Enh}), Enh(r_3) \neq null$ 
16:     $r_4 = \text{rand}(1, S_E), Enh(r_4) \neq null \text{ and } r_3 \neq r_4$ 
17:     $\rho_1 = \text{rand} < pop \rightarrow Pop_t(r_1) : Enh_t(r_3)$ 
18:     $\rho_2 = \text{rand} < pop \rightarrow Pop_t(r_2) : Enh_t(r_4)$ 
19:     $[o_1, o_2] = \text{crossover} + \text{mutation}(\rho_1, \rho_2)$ 
20:     $Q_t = Q_t \cup [o_1, o_2]$ 
21:  while  $i \leq S_{pop}/2$ 
22:   $Ref_t = Pop_t \cup Q_t$ 
23:   $(f_1, f_2, \dots) = \text{Sort-Non-Dominated}(Ref_t)$ 
24:  do
25:     $s_t = s_t \cup \phi \text{ and } i = i + 1$ 
26:  while  $|s_t| \geq N$ 
27:   $Lastfronttobeincluded f_l = f_j$ 
28:  if  $|s_t| = N$  then
29:     $Pop_{t+1} = s_t$ , break
30:  else
31:     $Pop_{t+1} = \bigcup_{j=1}^{l-1} F_j$ 
32:     $f_l = N - |Pop_{t+1}|$ 
33:     $Norm(f^n, s_t, Ref_s, Z^s, Z^a)$  Normalize
34:     $[\pi(s), d(s)] = \text{relate}(s_t, Ref_s) : \% \pi(s) : \pi(s)$  and  $s$ 
35:     $j \in \rho_j = Ref_s : \sum_{s \in s_t / f_l} (\pi(s) = j \rightarrow 1 : 0)$ 
36:     $Pop_{t+1} : \text{Niching}(K, \rho_j)$  from  $f_l$  select  $K$  members
    one at a time
37:  end if
38:   $[E_{t+1}, \mu_{t+1}] = \text{UpdateEnhanced}(Ref_s, Pop_{t+1},$ 
     $Enh_t, \mu_t)$ 
39:  while requisite condition doesn't match
  
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By using a selection operator, the multi-objective evolutionary algorithm selects the best solution, based upon its optimal value. The optimal value forms a new population. The iteration continues until the termination condition is met. This framework scrutinizes the influence of an enhanced offspring population archive when interchange recollection of operators has been utilized (that is when differential evolution (DE) are used instead of using Simulated Binary Crossover (SBX) polynomial mutation operators). The impact of an enhanced population archive has also be investigated when the creation of the offspring population requires neighboring enhanced solutions only. The effect of the penalization mechanism has

TABLE 1. Summary of related work on game theory based approaches for medical domain.

Paper	Technique/Theme	Advantages	Disadvantages	Domain
[17]	Analysis of health care systems along with interactions with individual agents using game theory.	Features including payment tables of individuals, detection of dysfunctional individuals, the causes of such dysfunctional cases and solutions to these problems are checked for the entire health care system.	Discussion on the game theory for complex scenarios covering qualitative strategies is not analyzed	Medical
[18]	Addresses the security effectiveness measures along with network performance for health systems by applying the game theory.	Efficient game theory model improved the performance by reducing latency to 25% as compared to static network policies.	Continuous monitoring of the network environment and capabilities of devices is still a challenge to meet the security and reliability of health data.	Medical
[19]	Comparison of the health care model of the general hospital with telemedicine using evolutionary game theory	The simulation results of this study conclude that people using telemedicine can get more benefits as compared to general hospital scenario.	Probabilistic approach and the results are deduced and concluded on assumptions	Medical
[20]	Game-theoretic signaling model to represent patient engagement after medical surgery.	Real patients' data is gathered and based upon that defined the 'engagement' in a more qualitative way. The two sides of the game include patient and physician.	Need modifications to cover a wide scope in the locality of patients along with portraying communication barriers using binary values	Medical
[21]	Analysis of cost-sharing health policies for individuals with chronic disease.	Framework is based on a game-theoretic scheme known as the stochastic Stackelberg game (SSG). Significant contributions include potentially personalized health insurance design for insured and health insurance	Implementing using a Bayesian SSG, where insurer should have complete information about insured for better decision-making.	Medical
[24]	Modelling and analyzing the interaction between an adversary and a decision-maker.	Liner support vector machine with Gaussian is used to classify the data. Convex optimization is utilized to prove the best response of the player	Performance parameters and mathematical models need to be incorporated for better results	Medical

also be analyzed to avoid favoritism to the solution being influenced to a single point.

The proposed framework improves the performance of a non-dominant sorting genetic algorithm by commissioning a bi-mechanism.

- 1) First commissioning of an enhanced archive to safeguard enhanced members of the population, which have otherwise been removed by the algorithm's selection procedure.
- 2) Second is the selection mechanism of a new parent to advance the diversity of the parent population.
- 3) Moreover, the member function enhancement and customization are also carried out by developing a comprehensive and specific fuzzy inference engine that is going to focus on two main objectives interpretability and accuracy.

Based on the quality of the solution set, EAs could generate varying results on every iteration. To resolve this issue, the average of all iterations is usually computed. Below sections have been added to describe the working of our proposed EA called MEAF by applying the game theory. This is to improve accuracy and interpretability at the same time and prove it through the Bayesian game theory.

III. RELATED WORK

Evolutionary game-theoretic models have also gained popularity in the past decade to model the strategic interaction between various entities of a given system. Some of the recent research studies related to applying game-theoretic models in the health domain have been listed below for quick reference to use our proposed model using the same theme. Table 1

presents a quick reference of applying game theory in medical domain.

The model proposed in [16] attempts to provide a survey for one of the applications of game theory in the blockchain. This work aims to evaluate various game models to address issues about network security e.g. Denial of Service attack (DoS), selfish mining and majority attack. In addition to this, it also covers issues related to mining management, blockchain economic and energy trading. This study still needs to address the issue of providing an incentive to game players to shift their strategy at the Nash Equilibrium state.

In [17] the research is conducted to perform an analysis of health care systems along with interactions of individual agents using game theory. This study checks the entire health care system and its features including payment tables of individuals, detection of dysfunctional individuals, the causes of such dysfunctional cases and solutions to these problems. In short, the research studies the entire health care system from the perspective of game theory. The study lacks to discuss the game theory for complex scenarios covering qualitative & quantitative strategies.

The research work proposed in [18] attempts to address the security effectiveness measures along with network performance for health systems by applying the game theory. The proposed approach has improved performance by reducing latency to 25% as compared to static network policies. Continuous monitoring of the network environment and capabilities of devices is still a challenge to meet the security and reliability of health data.

In [19] the study performs a comparison of the health care model of the general hospital to telemedicine. The proposed

approach uses evolutionary game theory to model the process. The simulation results of this study conclude that people using telemedicine can get more benefits as compared to general hospital scenario. A more realistic and fact-driven approach might be beneficial in the future because the current study is based on some assumptions to conclude the results. It is deemed essential to test the model in a depleted environment with a real-world scenario.

A game-theoretic signaling model is proposed in [20] that represent patient engagement after medical surgery. This model gathered real patients' data and based upon that defined the 'engagement' in a more qualitative way. The two sides of the game include patient and physician. The model proposed here needs to be modified to cover a wide scope in the locality of patients along with portraying communication barriers using binary values.

The framework proposed in [21] is an attempt to analyze cost-sharing health policies for individuals with chronic disease. This new framework is based on a game-theoretic scheme known as the Stochastic Stackelberg Game (SSG). The challenges that are addressed by this study include the modeling of the interaction between an insurer and insured along with deriving optimal cost-sharing strategies between insurer and disease progression. One of the significant contributions of this work includes its potentially personalized health insurance design for insured and health insurance. The future directions for this work may include implementing this study using a Bayesian SSG, where insurer should have complete information about insured for better decision-making.

The study proposed in [22] presents a game-theoretic model for infectious disease. This study has provided a qualitative model to represent that stigmatization of infected cases from a population can lead this infection to spread across the community. The proposed model still needs to be extended using mathematical proofs.

The work presented in [23] is based on a computational modeling framework that is efficient enough to model social dynamics that are involved in the human decision-making process. This study is an attempt to model the challenges of real-time social interactions that affect decision-making. The proposed method is based on a reinforcement learning scheme in combination with Gaussian processes to model real-time scenarios. This new approach to model social interaction presents a natural set of variables to model dynamic behavior and also sets a path towards further naturalistic modeling frameworks derived from the same.

A game-theoretic model is presented in [24] that is aimed at modeling and analyzing the interaction between an adversary and a decision-maker. The primary stage in this research is to classify the data using a linear support vector machine with Gaussian. It is demonstrated in this work that how the best response of players may be computed using convex optimization. The results of this approach are represented on a publicly available cardiovascular disease dataset. The results at the equilibrium position show that the performance of the

adversary is degraded considerably, which in turn reflects considerable improvement for the classifier. For future modifications, there is a need to improve the performance of the classifier further and testing the model on other gold standard datasets to remove biases.

The comprehensive research review presented in [25] is related to model the decision-making of individuals during various real-time situations. This remarkable review concludes that game theory is an effective and efficient tool to model human decision-making. The specialty of this review is that it highlights network-based modeling with imitation strategy as compared to compartmental modeling.

The research conducted in [26] is based on livestock data-sharing mechanism to control and eliminate Porcine Reproductive and Respiratory Syndrome virus (PRRSv). In this work, an attempt has been made to bring producers and veterinarians closer to the growth of the industry by implementing relevant surveillance systems, based on corresponding data sharing. This effort has proved to be supported by a great number of volunteers for the collective good of the livestock industry. Detailed literature review evinces that game theory is relatively a good choice to solve multi-objective problems. In the next section detailed evaluation of MEAF by amalgamating game theory is presented.

IV. MEAF USING GAME THEORY

The basic idea of game theory is based on multiple strategies defined by each player. In [27] a bi-objective game-theoretic model has been proposed using the Nash bargaining payoff distribution model. The multi-objective problem is to define an optimized solution for every player taking all strategies as input. This whole process is done interactively for every player and forms a strategy pool also known as a solution, which is called NASH EQUILIBRIUM (NE), which depicts that no player can attain additional edge based on their individual strategy by keeping the strategy of other players as unchanged.

A. NASH EQUILIBRIUM

In order to understand the concept behind the Nash Equilibrium, we can take the example of a game for two players. Let strategy of player 1 be M and N for the other player. These two strategies form a strategy pair and can be expressed as $S(M, N)$. The strategy pair (M, M) will be known as Nash Equilibrium if and only if the following is true for all $M \neq N$.

$$S(M, M) \geq S(M, N). \quad (1)$$

Many real-world problems can be listed that cover Nash Equilibrium. In [28] a multi-objective game model based on fuzzy goals has been proposed. In order to understand the concept further, consider the example of disease prediction using MEAF (Multi-objective Evolutionary Algorithm using Fuzzy Genetics); the two objectives for this EA are accuracy and interpretability. Depending upon the value of these parameters can help us to diagnose certain diseases

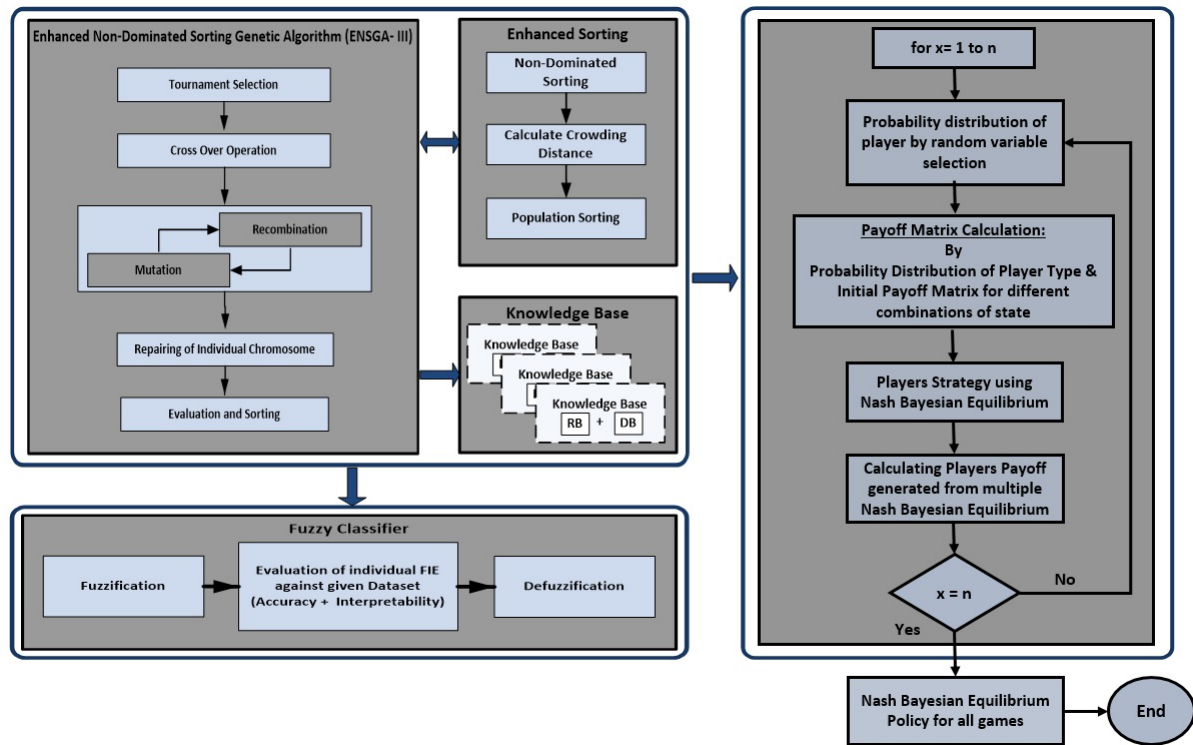


FIGURE 2. Flowchart of the Development Methodology for Bayesian Nash Equilibrium for CDSS.

using CDSS. The flowchart of the development methodology for Nash Bayesian Equilibrium for MEAF is presented in Figure 2.

B. EVOLUTIONARY GAME THEORY

Game theory has many applications from which one of them is the ‘Evolutionary Game Theory’. Evolutionary game theory has been used extensively to study single games applied to cancer [29]. This EGT can be used to describe various possibilities to solve the conflicting objectives for MEAF. All possible values of both objectives form the strategy pool, from which we need to find the Nash Equilibrium. This can lead to serving the purpose better. Rule-based evolutionary game theory has been applied in research [30]. Now we will look at two of the major parts of EGT, which are:

- 1) Evolutionary Stable Strategy (ESS).
- 2) Replicator Dynamics (RD)

1) EVOLUTIONARY STABLE STRATEGY

As the name suggests that it is the refined outcome of Nash Equilibrium, which is based on natural selection of code once it is present in a population. In the previous example stated above, the ESS is stable for a strategy if one the following conditions are met, for all $M \neq N$

$$S(M, M) \geq S(M, N). \tag{2}$$

or

$$S(M, M) = S(M, N) \& S(N, M) > S(M, N). \tag{3}$$

We can see that the first condition represents a strict Nash Equilibrium pair. In the second condition, we can see that strategy M is neutral than strategy N when we compare them for getting more advantage. For instance, if we consider players of a given population opting for playing certain strategy ‘a’ and let the other small share of population play using strategy ‘b’. In this case, we can come up with following payoffs for strategies a and b :

$$V(a, yb + (1 - y)a) \& V(b, yb(1 - y)a) \tag{4}$$

where ‘a’ and ‘b’ are strategies of players. Let us define some rules to further support the ESS for EGT.

Rule: For given strategies ‘a’ and ‘b’, strategy ‘a’ would be considered ES if, for every strategy $b \neq a$, certain $\bar{Y} \in (0, 1)$ exists to hold the inequality for all $Y \in (0, \bar{Y})$.

2) REPLICATOR DYNAMICS

This is an evolutionary model that enlightens the growth of various strategies used by different population groups. In [31] various strategies have been used to examine frequency-dependent interactions of cancer cells. This model works on the assumption that the population’s size is infinite, pairs of strategies are chosen randomly from population and time allocation is infinite.

The model in Figure 3 can be stated further as:

- 1) Since the process is iterative so it will shortlist only one strictly dominant strategy in the population over time.
- 2) This model deals with a population P.

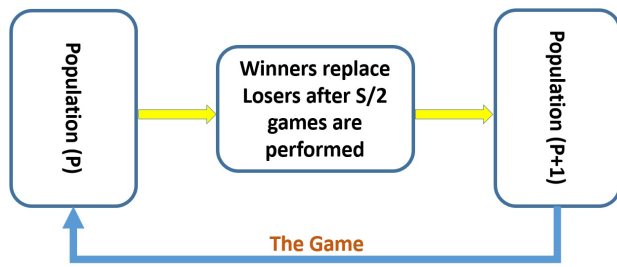


FIGURE 3. Evolution in Evolutionary Game Theory.

TABLE 2. Parameter list for game theory.

Symbol	Description
H_{CDSS}	Hospital CDSS
D	Doctor
P	Patient
T_p	Treatment Prescribed to to i^{th} patient
RT_p	Recommended Treatment by H_{CDSS} to Doctor
x	Affirmative
y	Rejection
p	Probability of Player b
$(1 - p)$	Probability of player a
P_{xx}	Patient prescribed treatment and has agreement on decision
P_{xy}	Patient prescribed treatment and has disagreement on decision
D_{xx}	Doctor offering treatment and patient has agreement
D_{xy}	Doctor not offering treatment and patient has agreement
μ	Utility of Patient
μ_1	Utility of Patient when has a disease and offered treatment
μ_4	Utility of Patient when has no disease and not offered treatment
δ	Utility of Doctor
δ_1	Utility of Doctor offering Treatment to Patient
δ_4	Utility of Doctor not offering Treatment to Patient

- 3) $S/2$ games are performed for a given generation. All strategies of the game are listed in pairs and tested for a stable strategy.
- 4) After each iteration, the winner replaces the loser.
- 5) After the above step, the new population $P + 1$ is generated and the process continues.

C. GAME THEORETIC SCENARIOS FOR CDSS

In this scenario, we study the benefits of relying on a deployed CDS system with respect to the overall reputation of a health institute. The analysis is performed in terms of a co-operative Bayesian game-theoretic model. The game is played between a patient who needs quick medical attention and a hospital administration who relies on medical experts as well as integrated multi-objective clinical data classification system for decision support. The parameter list of game theory model is presented in Table 2 below:

The scenario I of the game model has been listed below:

- 1) There are two players in the game, $N = D, P$.
- 2) T represents the type of players. $T = T_D, T_P$, where $T_P = Healthy(H), Sick(S)$ is the type space for patient P , i.e. P can be proven to be healthy or sick by D . While, D type is known to be $T_D = Honest$, as its strategy is to enhance its ability to yield correct decisions.

- 3) A presents the action set of players. As it is a cooperative incomplete information game, the possible actions P may take is to Accept or Reject the decision of D . For a P of type H we expect the same set of actions. On the other hand, as the D is always Honest the possible decisions it may take are to provide a decision for a further check-up or not.
- 4) The belief of D , is the probability distribution over the type of P . We consider that HP believes P of type S with probability p and it believes P of type H with probability $1 - p$.
- 5) The utility of the players is represented by set U , such that $U = (\delta, \mu)$.

The scenario II of the game model has been listed below:

- 1) There are two players in the game, $N = HA, D$.
- 2) T represents the type of the players. $T = T_{HA}, T_D$, where $T_D = Accept(A_x), Reject(A_y)$ is the type space for doctor D , i.e. D can accept or reject the assertions made by H_{CDSS} . While, H_{CDSS} type is known to be $T_{HA} = Honest$, as its strategy is to enhance its ability to yield correct decisions.
- 3) A presents the action set of players is not known. As it is a cooperative incomplete information game, the possible actions H_{CDSS} may take is to provide Correct or Incorrect information. For a D of type H we expect the same set of actions. On the other hand, as the H_{CDSS} is always Honest the possible decisions it may take are to provide a decision for further checkups or not.
- 4) The belief of H_{CDSS} , is the probability distribution over the type of D . We consider that $D = A_x$ believes D of type A_x with probability δ and it believes D of type A_y with probability $1 - \delta$.

The hospital CDSS (H_{CDSS}) holds data of patients including various attributes from the given population. The main objective of this game model is to perform disease diagnosis (D_d) for a patient (P_i) by using all resources available to the Hospital's clinical Decision Support System (H_{CDSS}). To define the payoff of the disease, it is crucial to mention here that for every iteration of monitoring patient records, there is an associated cost of penalty for the same. There are various possibilities for the model to be able to determine the sickness or healthiness status from type space consisting patients from the medical data repository. Based on the strategic behavior of disease D its expected utility is determined as under:

Table 3 present the payoff matrix highlighting players' incentive and penalization based on their deception type. The variable strategy between Doctor and Patient in which a doctor can and cannot offer treatment and similarly patient can accept or reject the decision deduced by the doctor.

Table 4 present the payoff matrix highlighting players' incentive and penalization based on their deception type. The variable strategy between H_{CDSS} and Doctor in which H_{CDSS} can and cannot recommend treatment and similarly doctor can accept or reject the recommendation deduced by the H_{CDSS} .

TABLE 3. Payoff matrix b/w Doctor D and Patient P.

Players	Doctor		
	Strategy	Treatment	No Treatment
Patient	Accepts	(EP[A = x, T _p = x], EP[T _p =x, A=x])	(EP[A = x, T _p = y], EP[T _p =y, A=x])
	Rejects	(EP[A = y, T _p = x], EP[T _p =y, A=x])	(EP[A = y, T _p = y], EP[T _p =y, A=y])

TABLE 4. Payoff Matrix b/w H_{CDSS} and Doctor D.

Players	H _{CDSS}		
	Strategy	Treatment	No Treatment
Doctor	Accepts	(EP[A = x, RT _p = x], EP[RT _p =x, A=x])	(EP[A = x, RT _p = y], EP[RT _p =y, A=x])
	Rejects	(EP[A = y, RT _p = x], EP[RT _p =y, A=x])	(EP[A = y, RT _p = y], EP[RT _p =y, A=y])

The confusion matrix b/w Doctor and Patient is as under:

$$\left\{ \begin{matrix} (P_{xx}, D_{xx}) & (P_{xy}, D_{xy}) \\ (P_{yx}, D_{yx}) & (P_{yy}, D_{yy}) \end{matrix} \right\} \quad (5)$$

Similarly, the confusion matrix b/w H_{CDSS} and Doctor is as under:

$$\left\{ \begin{matrix} (D_{xx}, H_{xx}) & (D_{xy}, H_{yx}) \\ (D_{yx}, H_{yx}) & (D_{yy}, H_{yy}) \end{matrix} \right\} \quad (6)$$

The patient must Accept the treatment if it has dominated strategy. The theorems for the player’s strategy of Nash equilibrium is explained below for better clarity of the scenario appraised:

Theorem 1:

Do
if ($P_{xx} > P_{yx}$) **AND** ($P_{xy} > P_{yy}$)
then
 A_x
else
 A_y
end if
While ($D_{xx} > D_{xy}$) **AND** ($D_{yx} > D_{yy}$)
 $T_p = x$

Similarly the Doctor must Accept the Recommended Treatment from H_{CDSS} under the same conditions as depicted in theorem above:

Theorem 2:

Do
if ($D_{xx} > D_{yx}$) **AND** ($D_{xy} > D_{yy}$)
then
 A_x
else
 A_y
end if
While ($H_{xx} > H_{xy}$) **AND** ($H_{yx} > H_{yy}$)
 $RT_p = x$

For simplicity and clarity, the detailed explanation of the game played between the doctor and the patient is presented. The expected payoff utility presented above is the various clinical decisions that include presence or absence of disease, acceptance or rejection of patient, Recommendation or non-recommendation of doctor and computational cost of the treatment. From the payoff matrix, we deduce that Doctors Utility is δ and the Patients utility be μ .

δ_1 means $T_p = x$ when Doctor suggests treatment on the presence of the disease and δ_4 means $T_p = y$ when Doctor suggests no treatment on the absence of the disease. The same phenomena is valid for the Patient and following inequalities hold:

$$\left\{ \begin{matrix} 0 \leq \delta_3 < \delta_2 < \delta_4 < \delta_1 \leq 1 \\ \delta_2 \leq \mu_4 \text{ \& } \delta_3 \leq \mu_1 \\ 0 \leq \mu_3 < \mu_2 < \mu_4 < \mu_1 \leq 1 \end{matrix} \right. \quad (7)$$

From Table 3 following scenario are played for options exercised by the Patient P and Doctor D:

$$\left\{ \begin{matrix} P_{xx} = E_p[A_x, T_p = x] = p * \mu_1 + (1-p) * (\mu_2(\mu_4 - \mu_2)) \\ P_{yx} = E_p[A_y, T_p = x] = p * \mu_3(\mu_1 - \mu_3) + (1-p) * \mu_4 \\ P_{xy} = E_p[A_x, T_p = y] = p * \mu_3(\mu_1 - \mu_3) + (1-p) * \mu_4 \\ P_{yy} = E_p[A_x, T_p = y] = p * \mu_3(\mu_1 - \mu_3) + (1-p) * (\mu_4) \\ (\mu_4 - \mu_2) \end{matrix} \right. \quad (8)$$

From Table 4 following scenario is played for options exercised by the Doctor D and H_{CDSS}:

$$\left\{ \begin{matrix} D_{xx} = E_p[A_x, T_p = x] = p * \delta_1 + (1-p) * (\delta_2(\delta_4 - \delta_2)) \\ D_{yx} = E_p[A_y, T_p = x] = p * \delta_3(\delta_1 - \delta_3) + (1-p) * \delta_4 \\ D_{xy} = E_p[A_x, T_p = y] = p * \delta_3(\delta_1 - \delta_3) + (1-p) * \delta_4 \\ D_{yy} = E_p[A_x, T_p = y] = p * \delta_3(\delta_1 - \delta_3) + (1-p) * (\delta_4) \\ (\delta_4 - \delta_2) \end{matrix} \right. \quad (9)$$

In this situation, players chose with the highest pay-off as an outcome using a mixed strategy. So, if the patient has the dominated strategy following holds:

$$\text{If } P_{xx} > P_{yx} \text{ AND } P_{xy} > P_{yy} \rightarrow A = x \quad (10)$$

and

$$\left\{ \begin{matrix} \text{If } D_{xx} > D_{xy} \text{ then the doctor} = T_p = x \\ \text{If } D_{xx} > D_{xy} \text{ then the doctor} = T_p = y \end{matrix} \right. \quad (11)$$

and

$$\text{If } P_{xx} > P_{yx} \text{ AND } P_{xy} < P_{yy} \rightarrow A = y \quad (12)$$

and

$$\left\{ \begin{matrix} \text{If } D_{yx} > D_{yy} \text{ then the doctor} = T_p = x \\ \text{If } D_{yx} < D_{yy} \text{ then the doctor} = T_p = y \end{matrix} \right. \quad (13)$$

Now solving the equation for mixed strategy:

If doctor choses $T_p = x$ probability p and $T_p = y$ probability $(1 - p)$ the patient will remain unconcerned about the strategy doctor chooses if and only if following hold:

$$E_p[A = x] = p * P_{xx} + (1 - p) * P_{xy} = p * (P_{xx} - P_{xy}) + P_{xy} \tag{14}$$

and

$$E_p[A = y] = p * P_{yx} + (1 - p) * P_{yy} = p * (P_{yx} - P_{yy}) + P_{yy} \tag{15}$$

In Nash Equilibrium following equality holds:

$$E_p[A = x] = E_p[A = y] \tag{16}$$

When we substitute the value in eq 16 from eq 14 and eq 15 we get the following:

$$p * (P_{xx} - P_{xy}) + P_{xy} = p * (P_{yx} - P_{yy}) + P_{yy} \tag{17}$$

$$p * [(P_{xx} - P_{xy}) - (P_{yx} - P_{yy})] = P_{yy} - P_{xy} \tag{18}$$

then

$$p = \frac{(P_{yy} - P_{xy})}{(P_{xx} - P_{xy}) + (P_{yy} - P_{xy})} \tag{19}$$

Similarly,

$$p = \frac{(D_{yy} - D_{xy})}{(D_{xx} - D_{xy}) + (D_{yx} - D_{yy})} \tag{20}$$

V. PERFORMANCE EVALUATION

Some very significant contributions have been implemented in the literature covering multi-objective evolutionary algorithms. Their inculcation with game theory has gained a very speedy recognition. Our proposed model MEAF has also been compared with a state-of-the-art technique available in the literature of multi-objective optimization that uses a fuzzy genetic model [32] which has outnumbered the results of 26 techniques of multi-objective classification arranged in 32 experimental setups applied to various benchmark datasets. NSGA-II technique is applied to learn both the parameters of fuzzy membership functions and the number of fuzzy rules in the rule base from the medical dataset. The graphical comparison of the proposed model highlights the phenomena of improved accuracy, interpretability, sensitivity and specificity as compared to its counterpart. Our technique achieved 98.97% accuracy with Wisconsin Breast Cancer Dataset, 83.52% accuracy with PIMA Indian Diabetes Dataset and 91.1% accuracy with Cleveland Heart Disease Dataset depicted in Figure 4, 5 and 6 respectively [33].

The improvement in the accuracy is due to the diversity in the selection process of the parent population by ingesting the penalization mechanism and retaining the offspring population in an archive to cover the complete solution space.

To evaluate the game model, the performance of the model is evaluated for both players. H_{CDSS} should be able to diagnose the disease accurately with minimum resource utilization. During the game, the iterative interaction of both players

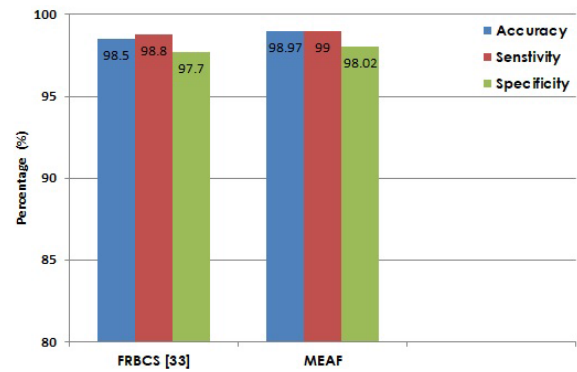


FIGURE 4. Wisconsin Breast Cancer - Accuracy, Sensitivity and Specificity Comparison with State of Art Techniques.

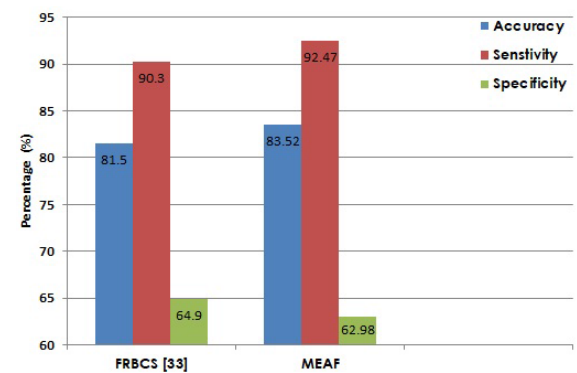


FIGURE 5. PIMA Indian Diabetes - Accuracy, Sensitivity and Specificity Comparison with State of Art Techniques.

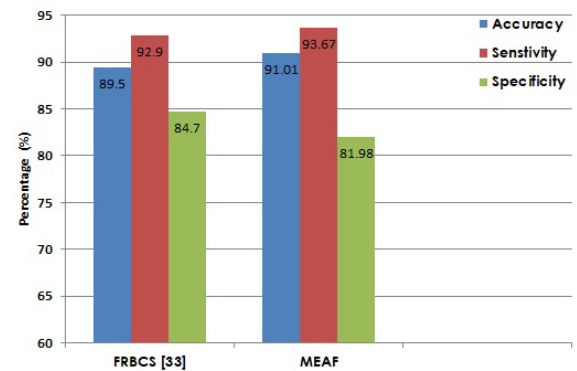


FIGURE 6. Cleveland Heart Disease - Accuracy, Sensitivity and Specificity Comparison with State of Art Techniques.

is checked by performing simulation so that the impact of various variables is validated over equilibrium strategies. This simulation is carried out using MATLAB. Since this game model attempts to perform classification to predict the relevant disease with minimum resource utilization therefore, it is crucial to evaluate the proposed model on the sensitivity measure for the datasets available. The following sections describe the impact of disease probability p on the sensitivity of the model that is the true positive rate and dis-

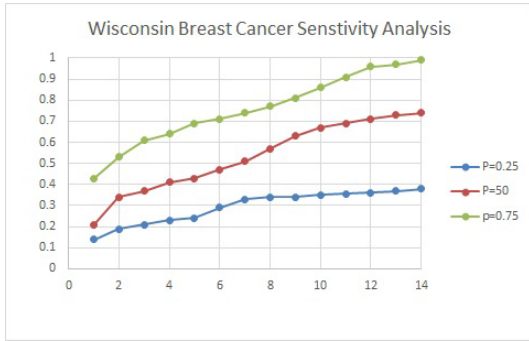


FIGURE 7. Sensitivity Analysis of WBCD.

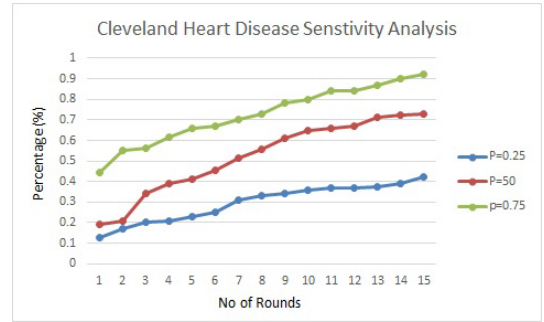


FIGURE 9. Sensitivity Analysis of CHDD.

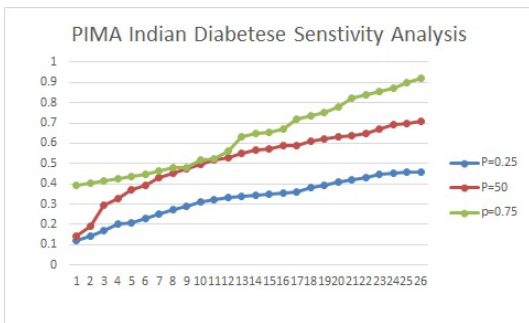


FIGURE 8. Sensitivity Analysis of PIDD.

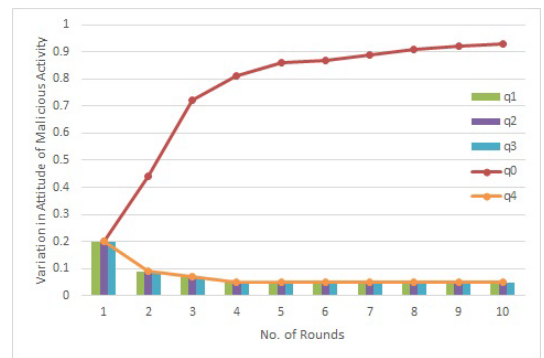


FIGURE 10. Impact of Monitoring Cost.

ease detection rate. Following sections describe each impact further:

A. SENSITIVITY ANALYSIS OF WISCONSIN BREAST CANCER DATASET

Wisconsin Breast Cancer Dataset (WBCD) contains the data of benign and malignant cases and is a multivariate dataset. The proportion of dataset has 35% malignant cases and 65% benign cases. The sensitivity of the game-theoretic model for this dataset after pre-processing is approximately 99% when the probability of malignancy is high such as $p=0.75$. However, the true positive ratio drops as the probability drops. The sensitivity analysis of WBCD is presented in Figure 7.

B. SENSITIVITY ANALYSIS OF PIMA INDIAN DIABETES DATASET

PIMA Indian Diabetes Dataset (PIDD) contains the data of positive and negative cases of diabetes patients. The proportion of the dataset has 35% positive cases and 65% negative cases. The sensitivity of the game-theoretic model for this dataset after pre-processing is approximately 92% when the probability of positive cases is high such as $p=0.75$. However, the true positive ratio drops as the probability drops. The sensitivity analysis of PIDD is presented in Figure 8.

C. SENSITIVITY ANALYSIS OF CLEVELAND HEART DISEASE DATASET

Cleveland Heart Disease Dataset (CHDD) contains the data of positive and negative cases of the patient of heart disease.

The proportion of the dataset has 46% positive cases and 54% negative cases. The sensitivity of the game-theoretic model for this dataset after pre-processing is approximately 92% when the probability of positive cases is high such as $p=0.75$. However, the true positive ratio drops as the probability drops. The sensitivity analysis of CHDD is presented in Figure 9.

D. IMPACT OF MONITORING COST

In this scenario, we attempt to investigate the impact of monitoring cost and the way it influences the union of belief of HA. In this scenario we have varied the worth of each patient record P. From obtained figures we can infer that cost of monitoring is kept constant whereas the worth of each H_{CDSS} is varied for various stages of the game. Figure 10 shows that the q_0 reaches to a maximum value for a lower cost.

E. IMPACT OF DETECTION RATE

In order to calculate the impact in rate of detection, it is crucial to keep track of number of games that are played by both players along with prior belief of H_{CDSS} represented by μ_0 . It is evident from Figure 11 that increase in detection rate increases the belief of H_{CDSS} parameter gradually. The value of belief approaches to 1 for game number 5 and higher.

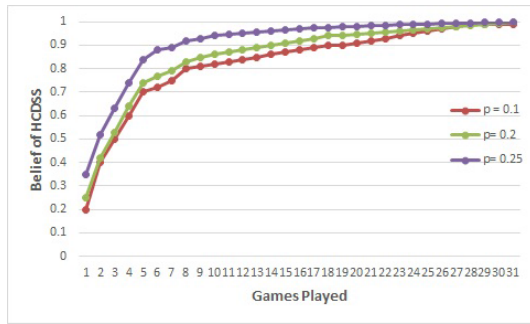


FIGURE 11. Impact of Detection Rate.

F. COMPUTATIONAL OVERHEAD

The results indicate that the proposed model has achieved remarkable accuracy and interpretability while also addressing the sensitivity and specificity issue that is the interim objectives achieved in the process of achieving the main objectives. It is important to mention here that the computational cost of a genetic algorithm mainly depends on the fitness function, selection operator and variation operator. Our approach uses the tournament selection procedure that is further optimized by the enhanced update mechanism. The algorithm yields $O(n \log n)$ computational cost in the best case scenario when all the above-mentioned parameters are selected optimally which is quite desirable in the complex evolutionary algorithms.

VI. DISCUSSION

The research highlighted in [34] is a very good effort in terms of applying game theory on health care scenarios. This research elaborates more on the behavioral aspect that is most of the time sentiment driven. The behavioral parameters used are trust, regret, guilt, and frustration. Both the players can hold these sentiments. However, our proposed model handles the scenario without incorporating any behavioral parameters. As the game is played between H_{CDSS} and the Patient where CDSS is invoked as an assistive tool to the doctor. So, the proposed model act as an observatory tool on the assertions and justifications made by the doctor and hospital administration. This makes our model more accurate and there is a very rare chance of any forgery by the stakeholder. Furthermore, comprehensive statistical analysis is provided to establish a belief that the results generated are not by chance or involve any biases. [21] presented a comprehensive game-theoretic model considering the association between cost-sharing and dynamic health outcomes for chronic heart disease by applying Stochastic Stackelberg Game (SSG). SSG needs to have all the information and knowledge of the player’s strategies to make the decision. However, our model has a superiority of handling this shortcoming by applying the Bayesian model that does not require prior knowledge. Another research [24] presents a game theory model applied on a linear support vector classifier that uses two classes positive and negative. The

TABLE 5. Error matrix of financial worth to monitor the variation of malicious activity attitude.

Attitude Variation	MAE	MBE	RMSE
$p = 0.75$	0.006	-0.02	0.013
$p = 0.50$	0.025	-0.008	0.038
$p = 0.25$	0.015	-0.010	0.054

TABLE 6. Error matrix of monitoring cost of variation in the attitude of malicious activity.

Attitude Variation	MAE	MBE	RMSE
q_0 vs q_1, q_2, q_3, q_4	0.684	-0.0684	0.736

TABLE 7. Error matrix of detection rate vs belief of H_{CDSS} .

Detection Rate	MAE	MBE	RMSE
$p=0.25$	0.0544	-0.05438	0.064163
$p=0.1$	0.0829	-0.08294	0.095391

research aims to identify the True Negative Probability (TNP) and False Negative Probability (FNP) by applying a convex optimization problem for best response dynamics to learn equilibrium. The framework is illustrated on publicly available cardiovascular dataset. Whereas, our proposed research is based on a relatively sophisticated multi-objective algorithm that uses Bayesian Nash Equilibrium due to incomplete information available between the players. Furthermore, rigorous experimental evaluations are conducted on three gold standard datasets available at UCI online repository (<https://archive.ics.uci.edu/ml/index.php>). The performance markers are accuracy, sensitivity (True Positive Rate) and specificity (False positive Rate). For the validation of sensitivity analysis, the evaluation of the proposed solution is carried out in terms of statistical measures like Mean Absolute Error (MAE), Mean Bias Error (MBE) and Root Mean Square Error (RMSE) in Table 5. The graph depicting the sensitivity complements the error matrix when a comparison is drawn between the probability of disease $p = 0.75, p = 0.50$ & $p = 0.25$. Similarly, the monitoring cost error matrix is depicted in Table 6 when the comparison is drawn between the q_0 vs q_1, q_2, q_3, q_4 .

To validate the model further, MAE, MBE, and RMSE for the detection rate are presented in Table 7.

The graph depicting the impact of detection rate enumerates that when $p = 0.25$ the belief of H_{CDSS} reaches a maximum on and around game 5 which is relatively quite fast as compared to the p values lower than 0.25 complementing the results of Table 7. Hence, the proposed solution achieves optimum belief even with relatively less probability.

VII. CONCLUSION

This paper presents a strategic interaction between Hospital CDSS and Disease on Patient Record P by involving a game-theoretic model. Depending upon the value of these parameters one can diagnose certain diseases using CDSS.

The basic idea of game theory is based on multiple strategies defined by each player. The multi-objective problem is to define an optimized solution for every player taking all strategies as input. This whole process is done interactively for every player and forms a strategy pool, which is called NASH EQUILIBRIUM (NE), meaning that no player can attain additional edge based on their individual strategy by keeping the strategy of other players as unchanged. In this study, sensitivity analysis of disease prediction with the renowned public dataset, monitoring cost and detection rate of both the players is evaluated by analyzing the finest behavioral analysis through Bayesian Nash Equilibrium. In the future, to further improve the accuracy and interpretability of objectives optimal utilization of polynomial mutation, usage of simulated binary crossover instead of differential evaluation and then applying game theory will be implemented to investigate the effect. We reckon that by doing so the solution space will converge to more than one reference point instead of converging to one reference point for more optimal decisions.

REFERENCES

- [1] N. Esfandiari, M. R. Babavalian, A.-M.-E. Moghadam, and V. K. Tabar, "Knowledge discovery in medicine: Current issue and future trend," *Expert Syst. Appl.*, vol. 41, no. 9, pp. 4434–4463, Jul. 2014.
- [2] M. Archetti and K. J. Pienta, "Cooperation among cancer cells: Applying game theory to cancer," *Nature Rev. Cancer*, vol. 19, no. 2, pp. 110–117, Feb. 2019.
- [3] H. Zare, M. Tavana, A. Mardani, S. Masoudian, and M. K. Saraji, "A hybrid data envelopment analysis and game theory model for performance measurement in healthcare," *Health Care Manage. Sci.*, vol. 22, no. 3, pp. 475–488, Sep. 2019.
- [4] Q. Li, M. Li, L. Lv, C. Guo, and K. Lu, "A new prediction model of infectious diseases with vaccination strategies based on evolutionary game theory," *Chaos, Solitons Fractals*, vol. 104, pp. 51–60, Nov. 2017.
- [5] T. Ganesan, P. Vasant, I. Elamvazuthi, and K. Z. K. Shaari, "Game-theoretic differential evolution for multiobjective optimization of green sand mould system," *Soft Comput.*, vol. 20, no. 8, pp. 3189–3200, Aug. 2016.
- [6] M. Ghobaei-Arani, A. A. Rahmani, A. Souri, and A. M. Rahmani, "A moth-flame optimization algorithm for Web service composition in cloud computing: Simulation and verification," *Softw., Pract. Exper.*, vol. 48, no. 10, pp. 1865–1892, 2018.
- [7] M. Masdari, S. Gharehpasha, M. Ghobaei-Arani, and V. Ghasemi, "Bio-inspired virtual machine placement schemes in cloud computing environment: Taxonomy, review, and future research directions," *Cluster Comput.*, pp. 1–31, Dec. 2019.
- [8] M. Ghobaei-Arani, A. A. Rahmani, M. S. Aslanpour, and S. E. Dashti, "CSA-WSC: Cuckoo search algorithm for Web service composition in cloud environments," *Soft Comput.*, vol. 22, no. 24, pp. 8353–8378, Dec. 2018.
- [9] M. Ghobaei-Arani and A. Souri, "LP-WSC: A linear programming approach for Web service composition in geographically distributed cloud environments," *J. Supercomput.*, vol. 75, no. 5, pp. 2603–2628, May 2019.
- [10] N. D. Vahed, M. Ghobaei-Arani, and A. Souri, "Multiobjective virtual machine placement mechanisms using nature-inspired Metaheuristic algorithms in cloud environments: A comprehensive review," *Int. J. Commun. Syst.*, vol. 32, no. 14, p. e4068, Sep. 2019.
- [11] R. Chai, A. Savvaris, A. Tsourdos, and S. Chai, "Multi-objective trajectory optimization of space manoeuvre vehicle using adaptive differential evolution and modified game theory," *Acta Astronautica*, vol. 136, pp. 273–280, Jul. 2017.
- [12] R. Khorsand, M. Ghobaei-Arani, and M. Ramezanpour, "A self-learning fuzzy approach for proactive resource provisioning in cloud environment," *Softw., Pract. Exper.*, vol. 49, no. 11, pp. 1618–1642, Nov. 2019.
- [13] R. Khorsand, M. Ghobaei-Arani, and M. Ramezanpour, "FAHP approach for autonomic resource provisioning of multitier applications in cloud computing environments," *Softw., Pract. Exper.*, vol. 48, no. 12, pp. 2147–2173, Dec. 2018.
- [14] E. Rafieyan, R. Khorsand, and M. Ramezanpour, "An adaptive scheduling approach based on integrated best-worst and VIKOR for cloud computing," *Comput. Ind. Eng.*, vol. 140, Feb. 2020, Art. no. 106272.
- [15] N. Najafabadi and M. Ramezanpour, "Mass center direction-based decision method for intraprediction in HEVC standard," *J. Real-Time Image Process.*, pp. 1–16, Mar. 2019.
- [16] Z. Liu, N. C. Luong, W. Wang, D. Niyato, P. Wang, Y.-C. Liang, and D. I. Kim, "A survey on applications of game theory in blockchain," 2019, *arXiv:1902.10865*. [Online]. Available: <https://arxiv.org/abs/1902.10865>
- [17] A. Bielecki and S. Nieszporska, "Analysis of healthcare systems by using systemic approach," *Complexity*, vol. 2019, pp. 1–12, Apr. 2019.
- [18] A. Arfaoui, A. Kribeche, S. M. Senouci, and M. Hamdi, "Game-based adaptive remote access VPN for IoT: Application to e-Health," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2018, pp. 1–7.
- [19] L. Zhou, "The research on the benefit of telemedicine to human based on evolutionary game theory," *Acta Sci. Med. Sci.*, vol. 2, pp. 42–50, 2018.
- [20] S. A. Castellanos, G. Buentello, D. Gutierrez-Meza, A. Forgues, L. Haubert, A. Artinyan, C. L. Macdonald, and J. W. Suliburk, "Use of game theory to model patient engagement after surgery: A qualitative analysis," *J. Surgical Res.*, vol. 221, pp. 69–76, Jan. 2018.
- [21] T.-Y. Ho, P. A. Fishman, and Z. B. Zabinsky, "Using a game-theoretic approach to design optimal health insurance for chronic disease," *IIEE Trans. Healthcare Syst. Eng.*, vol. 9, no. 1, pp. 26–40, Jan. 2019.
- [22] T. C. Reluga, R. A. Smith, and D. P. Hughes, "Dynamic and game theory of infectious disease stigmas," *J. Theor. Biol.*, vol. 476, pp. 95–107, Sep. 2019.
- [23] K. R. McDonald, W. F. Broderick, S. A. Huettel, and J. M. Pearson, "Bayesian nonparametric models characterize instantaneous strategies in a competitive dynamic game," *Nature Commun.*, vol. 10, no. 1, pp. 1–12, 2019.
- [24] F. Farokhi, "A game-theoretic approach to adversarial linear support vector classification," 2019, *arXiv:1906.09721*. [Online]. Available: <http://arxiv.org/abs/1906.09721>
- [25] S. L. Chang, M. Piraveenan, P. Pattison, and M. Prokopenko, "Game theoretic modelling of infectious disease dynamics and intervention methods: A mini-review," 2019, *arXiv:1901.04143*. [Online]. Available: <https://arxiv.org/abs/1901.04143>
- [26] A. M. Perez, D. C. L. Linhares, A. G. Arruda, K. VanderWaal, G. Machado, C. Vilalta, J. M. Sanhuesa, J. Torrison, M. Torremorell, and C. A. Corzo, "Individual or common good? Voluntary data sharing to inform disease surveillance systems in food animals," *Frontiers Veterinary Sci.*, vol. 6, p. 194, Jun. 2019.
- [27] M. Fahimullah, Y. Faheem, and N. Ahmad, "A bi-objective game-theoretic model for collaboration formation between software development firms," *PLoS ONE*, vol. 14, no. 7, 0, Art. no. e0219216.
- [28] W. Zhang, Y. Xing, and D. Qiu, "Multi-objective fuzzy bi-matrix game model: A multicriteria non-linear programming approach," *Symmetry*, vol. 9, no. 8, p. 159, 2017.
- [29] I. Kareva and G. Karev, "Natural selection between two games with applications to game theoretical models of cancer," *Bull. Math. Biol.*, vol. 81, pp. 2117–2132, Apr. 2019.
- [30] M. Alam, M. Tanaka, and J. Tanimoto, "A game theoretic approach to discuss the positive secondary effect of vaccination scheme in an infinite and well-mixed population," *Chaos, Solitons Fractals*, vol. 125, pp. 201–213, Aug. 2019.
- [31] J. West, M. Robertson-Tessi, K. Luddy, D. S. Park, D. F. K. Williamson, C. Harmon, H. T. Khong, J. Brown, and A. R. A. Anderson, "The immune checkpoint kick start: Optimization of neoadjuvant combination therapy using game theory," *JCO Clin. Cancer Informat.*, no. 3, pp. 1–12, Nov. 2019.
- [32] M. B. Gorzalczy and F. Rudziński, "Interpretable and accurate medical data classification—A multi-objective genetic-fuzzy optimization approach," *Expert Syst. Appl.*, vol. 71, pp. 26–39, Apr. 2017.
- [33] B. S. Raja and S. Asghar, "Using health data repositories for developing clinical system software: A multi-objective fuzzy genetic approach," *IET Softw.*, Feb. 2020.
- [34] B. Djulbegovic, I. Hozo, and J. P. A. Ioannidis, "Modern health care as a game theory problem," *Eur. J. Clin. Invest.*, vol. 45, no. 1, pp. 1–12, Jan. 2015.



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