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A Hybrid Feature Ranking Algorithm for Assisted Reproductive Technology Outcome Prediction

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HIGHLIGHTS

- Proposed a hybrid feature ranking algorithm named VIGAREA
- The proposed feature ranking algorithm gives importance to the individual feature as well as interaction between the features.
- The proposed VIGAREA can combine any number and type of feature selection methods along with information gain ratio

Abstract: In recent years, the emerging technology of machine learning has made vast strides in medicine. Machine learning-based clinical decision support systems assist doctors make efficient diagnoses and offer better prescriptions. Today, one of the greatest challenges for doctors worldwide is the treatment of infertility, with even the most sophisticated technology offering limited success. Currently, the Assisted Reproductive Technology (ART) in use is highly sophisticated technology that offers a success rate of 20%, depending on a slew of factors with complex relationships. With their capacity to analyze large and complex datasets, the application of machine learning techniques to predictions can maximize the ART success rate. This research work attempts a dynamic model for ART outcome prediction using incremental classifiernamed Ensemble of Heterogeneous Incremental Classifier (EHIC) in Machine Learning. In this paper,a new feature ranking algorithm named Voted Information Gain Attribute Rank Estimation Algorithm (VIGAREA) is proposed to enhance the performance of EHIC. The proposed VIGAREA is a combination of a number of feature selection methods and information gain ratio of each variable. It has the capability to rank the features based on its significance. The methodology and the way how the proposed VIGAREA is developed is presented. Experimental results proved that the EHIC with the proposed VIGAREA achieves the highest prediction with the ROC area of 95.5% for the ART dataset used for the research. The effectiveness of the proposed VIGAREA is checked with a range of miscellaneous feature selection methods and found that the proposed

feature ranking method VIGAREA performs optimally. Further, the performance of the proposed model is compared to that of existing models, and the findings show that the former outperforms the latter.

Keywords: Assisted Reproductive Technology (ART); Ensemble Learner; Incremental Classifiers; Feature Ranking.

INTRODUCTION

Machine learning (ML) is a combination of advanced statistics and Artificial Intelligence (AI), with the ability to extract previously unknown and potentially useful patterns from large databases, to be eventually converted into knowledge [1]. ML initially had takers in marketing and finance, and has since been applied in several fields, including healthcare. Presently, the status of human health worldwide calls for predictions to be made on one's physical condition in order to prevent disease, or determine the effects of treatment on people. Currently, a serious healthcare issue that needs to be addressed globally is human infertility. Infertility is witnessed, even in young couples, on account of numerous causes. Occasionally, however, the healthcare systems can attribute no specific reason for infertility [2]. Infertile couples face problems that affect their social and marital lives [2]. Infertility is conclusively addressed by Assistant Reproductive Technology (ART), a complex and biotechnologically advanced technique that helps couples conceive when conventional medical and surgical corrective procedures have failed [3]. However, ART treatments are expensive, time-consuming, complex and painful, with a very low success rate, given the involvement of a large number of variables. The predictive analytics of machine learning might be highly useful in this respect. Because of the existence of multiple determinants called features, and the existence of non-linear correlations between the features, the ART process requires advanced predictive models that are able to learn from a massive quantum of data and update themselves by obtaining data with new combinations of features [4]. Such predictive models assist doctors and patients to take corrective action, which improves the success rate. These factors call for a dynamic machine learning model for ART outcome prediction.

On the other hand, the predictive ability of a machine learning model depends on the features in the dataset and the algorithm used to build the model. The prediction ability is affected when the dataset has irrelevant features. Therefore, it is important to find influencing features in the dataset with a feature selection algorithm [4]. There exist a number of feature selection algorithms that work based on filter and wrapper methods. Filter methods work independent of the learning algorithm and computes the importance of variables by taking into account the relationship between a feature and a target variable. Wrapper methods works by evaluating all the possible combinations of features and select a subset of feature that is optimized for a given classification algorithm. Filter methods only consider the importance of a specific feature and not the results of interactions between features, whereas wrapper methods concentrate on the performance of the learning algorithm and overlook the importance of a specific feature [5-7]. A hybrid feature selection algorithm that considers both the importance of individual features and the interactions between the features may support in getting a better dynamic model for ART outcome prediction which was built by combining two incremental machine learning classifiers, the Instance-Based Learner (IB1) [14 -15] and the Averaged One Dependence Estimators (A1DE) updatable learner [16 – 19], by means of the ensemble method and was published in [8].

Hence, this research work propose a hybrid feature ranking algorithm named the Voted Information Gain Attribute Rank Estimation Algorithm (VIGAREA) that is capable of listing the influencing features by combining the results of different feature selection algorithm and information gain ratio of each feature. The performance of the proposed feature ranking algorithm is evaluated by comparing it with that of other feature selection methods.

Related work

Lu and coauthors [9] introduced a hybrid feature selection algorithm that combines the Mutual Information Maximization (MIM) and the Adaptive Genetic Algorithm (AGA) for gene expression data classification to eliminate the redundant samples and to reduce the dimension of the gene expression data.

Ahmad and Hayat [10] developed a high throughput computational model to identify the subGolgi proteins. Since the available dataset is imbalanced, Synthetic Minority Oversampling Technique (SMOTE) is utilized to balance the dataset and in addition, a condense feature space is formed by fusing the high rank features of eleven different feature selection techniques. The high rank features are selected through majority voting algorithm; Ahmed and coauthors [11] developed a hybrid feature selection method, which includes a filter and wrapper method for Human Activity Recognition (HAR) based on smart phone sensor data. The process uses a Sequential Floating Forward Search (SFFS) to extract desired features for better activity recognition. Shaban and coauthors [12] introduced a new COVID-19 diagnose strategy called COVID-19 Patients Detection Strategy (CPDS) in which, a new Hybrid Feature Selection Methodology (HFSM) is developed, that elects the most informative features from the chest Computed Tomography (CT) images of COVID-19 patients and non COVID-19 peoples. Ranjiniand coauthors [13], the authors of the current paper, examined the application of machine learning techniques to ART and discussed, qualitatively and quantitatively, the classifiers used for ART.

Motivation and Justification of the work

Assisted Reproductive Technology (ART) is a medical procedure that addresses infertility [5], and includes all treatments that handle human sperms, occytes or embryos in-vitro to establish pregnancy. In-Vitro Fertilization (IVF) and Intra-Cytoplasmic Sperm Injection (ICSI) are commonly used ART methods. In these procedures, several eggs are collected from a woman's ovary and fertilized with sperm to produce embryos. Of the developed embryos, one (or more) of the best-formed is transferred to the woman's uterus. Each stage of the procedure is critical. Also, the number and quality of the embryos transferred greatly impacts the success rate. The greatest challenge in this stage is embryo formation, which depends on factors like the number of oocytes collected and the immunological characteristic of sperm, as well as its morphology and motility. Predicting the probability of ART success prior to the procedure can help perfect features that affect fertility. This is done by identifying how significant the features are, thus increasing the probability of success.

Studies on ART outcome prediction used datasets with limited data from regional fertility centers, as well as static data. However, algorithms need to be trained using an adequate volume of data to produce a model with the ability to predict the correct influencing attribute on the outcome. The classifiers used in most studies worked with static data, though ART data is likely to be dynamic, with the influencing variables changing with respect to environmental characteristics. Consequently, a dynamic predictive model that describes all the influencing attributes is lacking. Furthermore, from the point of view of the couple/s in question, finding influencing attributes reduces the cost, pain and time taken for a number of ART-related tests needed for treatment Predicting the probability of success prior to commencing treatment strengthens, at a psychological level, the couple/s involved [23]. The problems listed above have motivated the building of a dynamic predictive model for ART outcome prediction. Dynamic models can be built using incremental classifiers in machine learning. The literature review makes it plain that using a combination of classifiers, rather than a single one, offers accurate predictions. So it is justified that this research work will use Ensemble of Heterogeneous Incremental Classifier (EHIC) which was implemented in [8] and propose a new feature ranking algorithm based on EHIC which has the capability to list the influencing feature which in turn may improve the performance of EHIC.

Outline of the work done

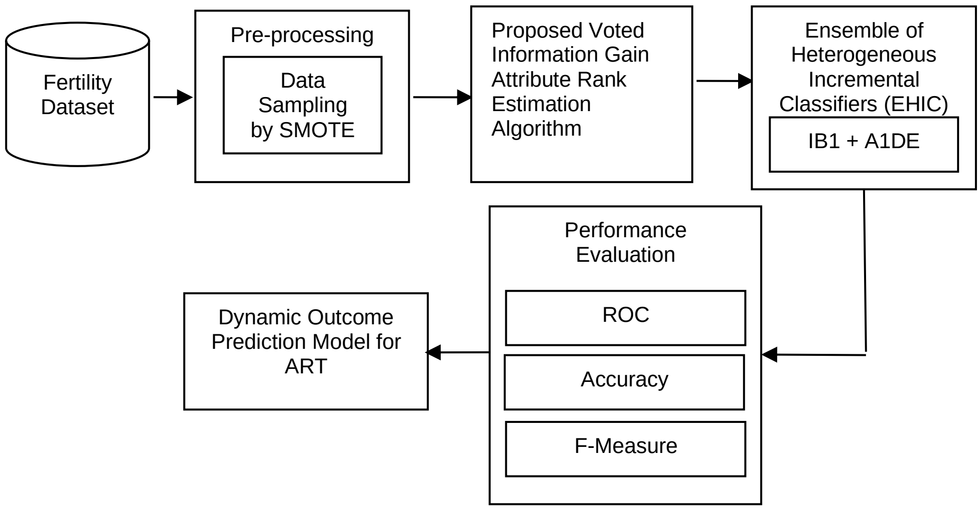

Figure 1. Outline of the work done

The dynamic outcome prediction model for ART is built by using the new classifier EHIC and the proposed new feature selection algorithm. The fertility dataset used for the experiment is balanced by SMOTE. The outline of the proposed work is shown in Figure 1.The rest of the paper is organized as follows. Section 2 presents the methodology of the proposed work. Section 3 presents the experimental results and discussions. Section 4 concludes the paper.

MATERIAL AND METHODS

The methodology of the proposed dynamic outcome prediction model for ART commences with pre-processing. Next, the proposed feature ranking algorithm finds the influencing feature. Finally, the outcome prediction model for ART is built, using the EHIC.

Pre-processing

In order to build the ART outcome prediction model, this research uses the ART (fertility) dataset maintained by the Human Fertilization and Embryo Authority (HFEA). The dataset comprises a more records for negative results and a minimal number for positive results, rendering it imbalanced. An imbalanced dataset impacts the performance of the classifiers. Experiments conducted [24] and corroborated by findings from the literature show that the SMOTE is best for balancing data [20 - 21][24]. As a result, the ART dataset is balanced by the SMOTE.

Feature Selection: Proposed Voted Information Gain Attribute Rank Estimation Algorithm (VIGAREA)

The objective of this work is to propose a hybrid feature ranking algorithm with the ability to extract the influencing attribute by assigning weights to features (attributes). The novelty of the proposed algorithm lies in the calculation of weights for the features. In the real world dataset, especially in medical dataset, most of the features will be interrelated and adopting the existing filter type feature ranking methods which mostly depend on Univariate measure for ranking become inappropriate. Wrapper based feature selection methods may also ignore some important features since the selection of influential features depend on the performance of classifiers. Hence, instead of depending on a single feature selection method, the proposed work tries to take advantage of several feature selection methods. This research uses a number of feature selection methods, with the top vote going to features selected by the maximum number of feature selection methods so the best is selected. The votes for a particular feature are calculated by counting the number of feature selection methods choosing the said feature. To preserve the importance of individual features, the Information Gain Ratio (IGR) of each feature is calculated simultaneously. The weights for each featuresare calculated by multiplying the information gain ratio of each feature with the votes calculated for each. The weights for each feature are converted into normalized weights and checked with a certain threshold. Finally, features with a weight greater than or equal to the threshold value are selected as influencing features.

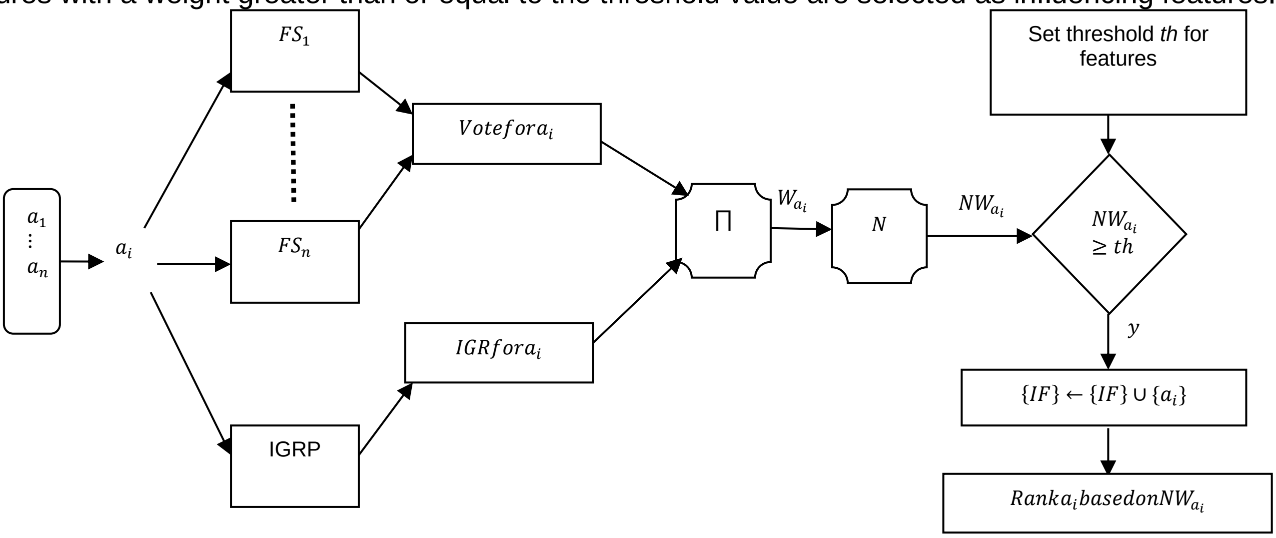

Figure 2. Block Diagram for the Proposed Voted Information Gain Attribute Rank Estimation Algorithm.

The schematic representation of the proposed VIGAREA is shown in Figure. 2, where $a_1 \ldots a_n$ represents the list of attributes (features) which is given as input to the various feature selection algorithm and a_i represents a single attribute and the value of i varies from $1\ ton$. $FS_1 \ldots FS_n$ represents the list of feature selection algorithms that are selected for vote calculation. $Votefora_i$ represents the vote of each feature which is calculated by counting the number of feature selection methods that choose the particular feature. IGRP represents the procedure for calculating IGR for each feature. IGR for each feature is represented by $IGRfora_i$. $\prod$ calculates the weight W_{a_i} for each feature by multiplying vote and IGR of each feature. The calculated weight $W_{a_i}$for each feature is converted into normalized weight NW_{a_i} by the normalization function N. The threshold limit $th$for normalized weight will be set by passing the set of features satisfying varying criteria to the classifier. The attributes a_i having the normalized weight NW_{a_i} above and equal to threshold th will be added to the Influencing Feature Subset $\{IF\}$. Finally, the attributes will be ranked based on normalized weight.

List of Feature Selection Methods Used

This research uses various feature selection methods both from Filter Methods and Wrapper Methods. For filter approach, Correlation Feature Selection (CFS)filter methodis used in combination with the three search methods namely Best First Search (BFS), Greedy and Particle Swarm Optimization (PSO). For wrapper method four search methods namely Greedy, BFS, Incremental Wrapper Subset Selection (IWSS) and IWSS with embedded NB is used [25 – 31]. The classifiers used for wrapper method are EHIC, A1DE Updatable and IB1. Totally fifteen combinations of methods are used. Hence in this research the total number votes calculated for each attribute will be 15.

Information Gain Ratio (IGR)

Information Gain (IG) represents the average amount of information about the class value contained in a feature or attribute value [32]. IG gives mutual information between the class and attribute. It is a symmetrical measure of dependency between two attributes and selects candidate features with more information which is identified with the help of entropy[33].The IG values of features provide reasonable knowledge to reduce the search space for feature subset selection but it favours features with more values even though they are not informative. IG is defined as

$$IG(Attribute) = IG(Class, Attribute) = H(Class) - H(Class|Attribute)$$

where, $H(Class)$ is called as the Entropy of the Class and is calculates as

$$H(Class) = -\sum_{i=1}^{No.of Class} P(Class_i).\, log_2\, P(\,Class_i)$$

is the Shannon's entropy and

$$H(Class|Attribute) = -\sum_j P(Attributes_j)\sum_i P\left(Class_i\middle|Attribute_j\right) log_2\, P\left(Class_i\middle|Attribute_j\right)$$

IGRevaluates the worth of an attribute by measuring the gain ratio with respect to the class. It is a non-symmetrical measure that is introduced to balance the bias of the IG (5). IGR is given as

$$IGR(Class, Attribute) = \frac{\left(H(Class) - \ H(Class|Attribute)\right)}{H(Attribute)}$$

where,

$$H(Attribute) = -\sum_{j=1} P\left(Attribute_j\right).\, log_2\, P(Attribute_j)$$

where$j$ is the number of different values of the attributes.

In IGR, when a class has to be predicted, it normalizes the IG by dividing by the entropy of that attribute, and vice versa and hence, the IGR values always fall in the range [0, 1]. A value of IGR = 1 indicates that the information of the particular attribute completely predicts the class, and A value of IGR = 0 indicates that there is no relation between that attribute and the class.

Algorithm: Proposed Voted Information Gain Attribute Rank Estimation Algorithm

$\boldsymbol{Input}$: $Attrinutesset\{a_1, a_2, \dots . a_n\} \in TrainingSetD = \{x_i, y_i\}_{i=1}^{m}$
: $ListofFSalgorithmsFS = \{f_1, f_2, \cdots, f_n\}$
$\boldsymbol{Output}$: $RankedInfluencedAttributesetIF$
1. $SelectthelistofFeatureSelectionAlgorithmFS = \{f_1, f_2, f_3 \dots . f_n\}$
2. $Foreachattributea_1, a_2, \dots . a_n do$
   a. $ForeachFSdo$
   $if\, a_i isselectedby f_i then$
   $vote_{a_i} = vote_{a_i} + 1$
   $EndFor$
   b. $ClaculateInformationGainRatioforeachattribute$
   $IGR_i = InformationGainRatio(a_i)$
   c. $CalculateWeightforeachattribute$
   $weight_{a_i} = IGR_i \times vote_{a_i}$
$EndFor$
3. $CalculateNormalizedWeightforeachattribute$
$$NormalizedWeight_{a_i} = \frac{weight_{a_i}}{\sum weight_{a_i}}$$
4. $OrderAttributesa_i basedonNormalizedWeightandassignRank$
5. $FindthethresholdlimitbyPassingattributestotheselectedclassifier$
   a. $Evaluatetheperformanceoftheclassifier.$
   b. $Whentheperformanceoftheclassifierstartstodegrade, setthethresholdvalue.$
6. $ChoosetheattributeshavingtheNormalizedweightaboveandequaltothreshold$ $asinfluencingattribute$ {IF}

Classifier: Ensemble of Incremental Classifier for ART Outcome Prediction

The ensemble of heterogeneous incremental classifier (EHIC) which was proposed by the authors in [8] is used for classification. The performance of the EHIC may be enhanced by supplying influenced feature subset. The block diagram for the proposed model for ART outcome prediction is shown in Figure. 3.

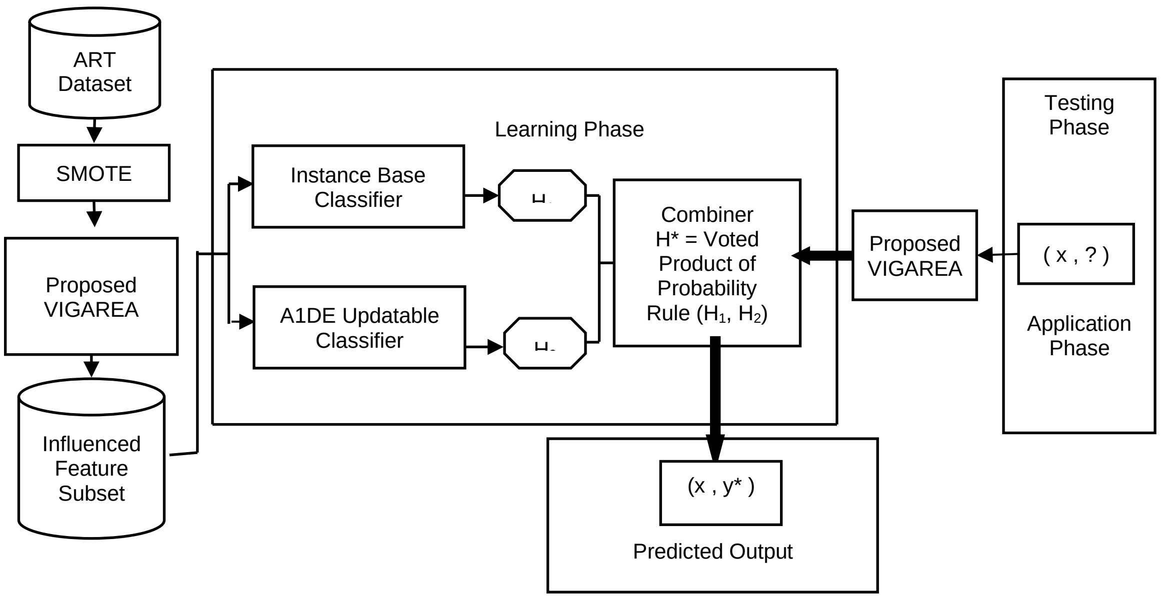

Figure 3. Block Diagram of Dynamic Outcome PredictionModel for ART.

RESULTS

This section explains the working of the proposed feature ranking algorithm, VIGAREA, in finding influencing features, and undertakes an evaluation of its performance. To evaluate the performance of the classifiers, the ROC is taken as a high-priority metric throughout the experiment, since it produces unbiased reports even for imbalanced datasets. The HFEA maintains ART treatment data which is available at https://www.hfea.gov.uk. Total of 16383 records with 52 ART-related attributes are used for this research [40].

Working of Proposed Feature Ranking Algorithm

The performance of the machine learning algorithm depends on the quality of the data operated on, and that of a model may be enhanced by providing an adequate quantum of relevant information. The HFEA dataset used contains an adequate number of instances and is to be checked to ascertain if its contents comprise relevant or extraneous and irrelevant information. This task is executed using a number of feature selection methods that are chosen and applied to the HFEA dataset to find the influencing features. The resultant influencing feature for each method is shown as tick mark (✓) in Table 1. The last column of the Table 1 shows the number of feature selection method selects a particular feature, which is represented as a vote for the attribute. Each tick in Table 1 indicates the selection of a particular attribute by a particular feature selection method.The number of selected features by each method is shown within the parenthesis in the header row in Table 1.

Table 1. Attribute Selected By Various Feature Selection Method

List of attributes in the HFEA Dataset	List of Selected Attributes with Feature Selection															Vote for Attribute
	Filter Method			Wrapper Method												
				Greedy			Best First			IWSS			IWSS with embedded NB			
	CFS/BFS (7)	CFS/Greedy (7)	CFS/ PSO (9)	EHIC (15)	A1DE (25)	IB1 (8)	EHIC (15)	A1DE (25)	IB1 (8)	EHIC (36)	A1DE (26)	IB1 (36)	EHIC (18)	A1DE (18)	IB1 (18)	
Patient Age at Treatment	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	**15**
No. of Previous cycles, Both IVF and DI								✓		✓		✓				**3**
Total Number of Previous treatments, Both IVF DI at clinic										✓		✓				**2**
Total number of Previous IVF cycles	✓	✓		✓	✓		✓			✓	✓	✓	✓	✓	✓	**11**
Total number of Previous DI cycles				✓	✓		✓				✓		✓	✓	✓	**7**
Total no. of prev. pregnancy, Both IVF&DI										✓	✓	✓				**3**
Total number of IVF pregnancies								✓			✓					**2**
Total number of DI pregnancies	✓	✓								✓			✓	✓	✓	**6**
Total number of live births - conceived through IVF/ DI					✓					✓						**2**
Total number of live births - conceived through IVF					✓	✓		✓	✓							**4**
Total number of live births - conceived through DI												✓				**1**
ToI - Female Primary										✓		✓				**2**
ToI - Female Secondary										✓	✓	✓				**3**
ToI- Male Primary										✓		✓				**2**
ToI - Male Secondary					✓			✓		✓	✓	✓				**5**
ToI -Couple Primary								✓		✓		✓				**3**
ToI -Couple Secondary				✓			✓									**2**
CoI - Tubal disease				✓	✓		✓	✓		✓	✓	✓	✓	✓	✓	**10**
CoI - Ovulatory Disorder					✓			✓		✓	✓	✓				**5**
CoI - Male Factor				✓			✓			✓		✓	✓	✓	✓	**7**
CoI - Patient Unexplained								✓		✓	✓	✓	✓	✓	✓	**7**
CoI – Endometriosis				✓	✓		✓			✓	✓	✓	✓	✓	✓	**9**
CoI - Cervical factors	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	**15**
CoI - Female Factors								✓								**1**
CoI - Partner Sperm Concentration				✓	✓		✓	✓		✓	✓	✓	✓	✓	✓	**10**
CoI- Partner Sperm Morphology			✓		✓			✓		✓	✓	✓	✓	✓	✓	**9**

Table 1. Cont.

List of attributes in the HFEA Dataset	List of Selected Attributes with Feature Selection																Vote for Attribute
	Filter Method			Wrapper Method													
				Greedy			Best First			IWSS			IWSS with embedded NB				
	CFS/BFS (7)	CFS/Greedy (7)	CFS/ PSO (9)	EHIC (15)	A1DE (25)	IB1 (8)	EHIC (15)	A1DE (25)	IB1 (8)	EHIC (36)	A1DE (26)	IB1 (36)	EHIC (18)	A1DE (18)	IB1 (18)		
CoI - Partner Sperm Motility	✓	✓	✓	✓	✓		✓			✓	✓	✓	✓	✓	✓		**12**
CoI- Partner Sperm Immunological factors	✓	✓	✓		✓	✓		✓	✓	✓	✓	✓	✓	✓	✓		**13**
Stimulation used					✓	✓		✓	✓			✓					**5**
Type - Ovulation Induction										✓	✓	✓					**3**
Donated embryo										✓		✓					**2**
Type of treatment - IVF / DI																	**0**
Specific treatment type												✓					**1**
Egg Source					✓					✓		✓					**3**
Sperm From					✓			✓		✓	✓						**4**
Fresh Cycle								✓				✓					**2**
Frozen Cycle						✓			✓			✓					**3**
Fresh Eggs Collected					✓			✓		✓	✓						**4**
Fresh Eggs Stored																	**0**
Total Eggs Mixed					✓	✓			✓	✓	✓	✓	✓	✓	✓		**9**
Eggs Mixed With Partner Sperm				✓	✓		✓	✓		✓	✓	✓					**7**
Eggs Mixed With Donor sperm			✓					✓		✓		✓					**4**
Total Embryos Created			✓		✓			✓		✓	✓	✓					**6**
Eggs Micro-injected (ICSI)			✓	✓	✓		✓	✓		✓	✓		✓	✓	✓		**10**
Embryos from ICSI				✓			✓			✓		✓	✓	✓	✓		**7**
Total Embryos Thawed																	**0**
Embryos Transferred	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		**15**
Embryos Transferred from ICSI																	**0**
Embryos Stored For Use By Patient				✓	✓		✓	✓		✓	✓	✓	✓	✓	✓		**10**
Embryos (ICSI) Stored By Patient																	**0**
Year of Treatment					✓			✓		✓	✓	✓					**5**

Once the vote is calculated, the next step is to calculate the weight for each feature which is done by multiplying the calculated vote of each feature (Table 1) with the information gain ratio of each feature.Next, the calculated weight is converted into a normalized weight, based on which ranks are assigned to the attributes. Table 2 shows how the proposed feature selection method calculates the weight, how the calculated weight is converted to a normalized weight, and how a rank is assigned to each attribute in descending order of the calculated normalized weight.

Table 2. Attribute Ranking by the Proposed Feature Ranking Method

List of ordered attributes	Vote	IGR	Weight = Vote × IGR	Normalized Weight (NW)	Rounded NW	Rank
Embryos Transferred	15	0.096617921	1.449268808	0.210013345	0.21	1
CoI - Cervical factors	15	0.068534536	1.028018039	0.148969953	0.15	2
CoI -Partner Sperm Immunological factors	13	0.060430488	0.785596348	0.113840659	0.11	3
CoI - Partner Sperm Motility	12	0.043533818	0.522405813	0.075701755	0.08	4
Eggs Micro-injected	10	0.041999841	0.41999841	0.060861912	0.06	5
CoI- Partner Sperm Morphology	9	0.044193765	0.397743881	0.057637011	0.06	6
Patient Age at Treatment	15	0.022068487	0.331027299	0.047969121	0.05	7
Embryos from Eggs Micro-injected	7	0.036021257	0.252148799	0.036538848	0.04	8

Table 2. Cont.

List of ordered attributes	Vote	IGR	Weight = Vote × IGR	Normalized Weight (NW)	Rounded NW	Rank
CoI – Endometriosis	9	0.021505517	0.193549653	0.028047254	0.03	9
Total number of DI pregnancies	6	0.03176928	0.190615682	0.027622092	0.03	10
Total Embryos Created	6	0.023753213	0.142519275	0.020652449	0.02	11
CoI - Partner Sperm Concentration	10	0.012721566	0.12721566	0.018434804	0.02	12
Total Number of Previous DI cycles	7	0.017601871	0.123213097	0.017854793	0.02	13
Total Eggs Mixed	9	0.012988621	0.116897587	0.016939613	0.02	14
Total Number of Previous IVF cycles	11	0.010030605	0.110336658	0.01598887	0.02	15
Embryos Stored For Use By Patient	10	0.010553361	0.105533613	0.015292861	0.02	16
Eggs Mixed With Partner Sperm	7	0.009061926	0.063433484	0.009192138	0.01	17
Eggs Mixed With Donor sperm	4	0.015766382	0.063065527	0.009138817	0.01	18
CoI - Ovulatory Disorder	5	0.011868041	0.059340207	0.008598981	0.01	19
Total live births - conceived through DI	1	0.056871178	0.056871178	0.008241195	0.01	20
Fresh Eggs Collected	4	0.012921656	0.051686623	0.007489902	0.01	21
ToI - Male Secondary	5	0.007609798	0.038048989	0.005513674	0.01	22
Total no. of previous pregnancy, Both IVF& DI	3	0.010394281	0.031182843	0.004518702	0.00	23
CoI - Tubal disease	10	0.00302066	0.030206604	0.004377235	0.00	24
Total no. of Prev. cycles, Both IVF and DI	3	0.007602331	0.022806992	0.003304958	0.00	25
Total no. of live births - conceived through IVF	4	0.005026715	0.020106862	0.002913683	0.00	26
Total number of IVF pregnancies	2	0.009343884	0.018687768	0.002708042	0.00	27
ToI - Female Secondary	3	0.006166713	0.018500138	0.002680852	0.00	28
CoI - Patient Unexplained	7	0.002587468	0.018112275	0.002624647	0.00	29
Sperm From	4	0.004132463	0.016529851	0.002395338	0.00	30
Total Number of Previous treatments, Both IVF and DI at clinic	2	0.007943271	0.015886542	0.002302117	0.00	31
Specific treatment type	1	0.013936589	0.013936589	0.002019549	0.00	32
Stimulation used	5	0.002746338	0.013731689	0.001989857	0.00	33
Total number of live births - conceived through IVF or DI	2	0.00591331	0.011826621	0.001713794	0.00	34
Type of Ovulation Induction	3	0.002757254	0.008271763	0.00119866	0.00	35
Frozen Cycle	3	0.002451643	0.00735493	0.001065802	0.00	36
ToI -Couple Secondary	2	0.00317358	0.00634716	0.000919766	0.00	37
Donated embryo	2	0.002248727	0.004497454	0.000651725	0.00	38
Fresh Cycle	2	0.002106672	0.004213345	0.000610555	0.00	39
Year of Treatment	5	0.000784768	0.003923839	0.000568603	0.00	40
Egg Source	3	0.001000979	0.003002936	0.000435155	0.00	41
CoI - Male Factor	7	0.000278089	0.001946622	0.000282085	0.00	42
ToI - Male Primary	2	0.000572012	0.001144024	0.00016578	0.00	43
ToI -Couple Primary	3	3.00E-05	9.00E-05	1.30E-05	0.00	44
ToI - Female Primary	2	1.76E-09	3.52E-09	5.10E-10	0.00	45
CoI - Female Factors	1	0	0	0	0.00	46
Type of treatment - IVF or DI	0	0	0	0	0.00	47
Fresh Eggs Stored	0	0	0	0	0.00	48
Total Embryos Thawed	0	0	0	0	0.00	49
Embryos Transferred from Eggs Micro-injected	0	0	0	0	0.00	50
Embryos (from ICSI) Stored	0	0	0	0	0.00	51
			$\sum \text{weight} =$ 6.900841517	1	1	

The results from Table 2 show that the proposed feature selection method VIGAREA takes advantage of both the filter and wrapper methods. Given that the IGR calculation does not depend on the classifier used, the working principle in operation is the filter approach, whereas both the filter and wrapper methods are used for vote calculation. Thus, the proposed feature selection method works well as a hybrid.

Despite the efficacy of the new feature ranking algorithm proposed, the goal of the experiment is to find the influencing features of the ART dataset for EHIC. To this end, a new experiment is conducted by setting several criteria to find the threshold limit for the attribute. Attributes satisfying the specified criteria, based on the normalized weight, are passed through the EHIC and the performance of the EHIC is evaluated. The results of the experiments are shown in Table 3.

Table 3 shows that the EHIC performs well for criteria where the normalized weight for an attribute less than 0.01 is removed. Hence the threshold limit is set to 0.01, and attributes with a normalized weight above and equal to 0.01 are chosen as influencing features. According to the proposed feature selection method, attributes with a rank from 1 to 22 are selected as influencing features. It is also evident that the ROC value for the proposed EHIC has risen to 95.5.

Table 3. Finding the Threshold Value for Normalized Weight (NW) to Choose Influencing Features

Attributes	No. of Attributes	Performance Metrics (%)								Error	Time (S)
		Accuracy	TPR	FPR	Precision	Recall	F-Measure	ROC Area	PRC Area		
All	51	85.0	85	18.4	86.1	85.0	0.846	94.1	94.1	0.15	0.08
NW = 0	45	85.0	85	18.4	86.1	85.0	0.846	94.1	94.1	0.15	0.08
NW < 0.01	22	87.6	88	12.5	88.4	87.6	0.875	95.5	95.5	0.13	0.05
NW < 0.02	16	82.7	83	17.4	84.0	82.7	0.825	90.6	90.7	0.18	0.05
NW < 0.03	11	75.9	76	24.3	77.3	75.9	0.756	82.4	81.9	0.28	0.05

Evaluation of the Proposed Model for each Classes of ART Dataset

The following experiment checks the applicability of the model for individual classes in the ART dataset. The class variable of the HFEA ART dataset is *Live Birth Occurrence* which is a binary class variable (1 - *Live Birth;* 0 - *Not a Live Birth)*. The predictive model must predict all the classes equally; and not skew towards a particular class. To check the stability of predicting both classes equally, the evaluation of the dynamic model for each class isshown in Table 4.

Table 4. Evaluation of the Proposed Model for each Classes of ART Dataset

Performance Metric (%)	Values for class variable Live Birth Occurrence		Weighted Average of both class
	0 – Not Live Birth	1 – Live Birth	
TP Rate	80.0	95.0	87.6
Precision	94.0	82.8	88.4
Recall	80.0	95.0	87.6
F-Measure	85.5	88.5	87.5
ROC Area	95.5	95.5	95.5
PRC Area	95.1	95.8	95.5
FP Rate	5	20	12.5

From Table 4, it is clear that the proposed model is not skewed towards a particular class, and so it is recommended that the EHIC based on the hybrid feature ranking algorithm be used for ART outcome prediction.

A Performance Evaluation of the VIGAREA with other Feature Selection Methods

Without relying on the existing feature selection method for the EHIC, this research proposes a new feature ranking method for choosing influential attributes. There is, however, a need to validate the performance of the proposed VIGAREA by comparing it with other feature selection algorithms, as well as those without feature selection, for both the base learners IB1 and A1DE Updateable and the EHIC, as listed in Table 5. The last row of Table 5 shows the number of Influencing Features (IF) selected by each method. It is apparent from Table 5 that the proposed feature ranking algorithm performs best with only 22 selected features. It is followed by the Incremental Wrapper Subset Selection (IWSS) method with good results.

Further, Table 5 shows that the EHIC and base learners produce the highest results for the proposed feature ranking method, proving that it is best suited to ART outcome prediction.

Table 5. Comparison of the Proposed Feature Ranking Method with Various Feature Selection Methods.

Performance Metric (%)	Without Feature Selection			Filter Method			Wrapper Method												Proposed Feature Ranking Method		
				BFS	Greedy	PSO	Greedy			Best First			IWSS			IWSS with embedded NB					
	EHIC	A1DE Updatable	IB1	EHIC	EHIC	EHIC	EHIC	A1DE Updatable	IB1	EHIC	A1DE Updatable	IB1	EHIC	A1DE Updatable	IB1	EHIC	A1DE Updatable	IB1	EHIC	A1DE Updatable	IB1
Accuracy	85	77	86	73	73	75	78	78	69	78	78	69	86	78	86	81	76	80	88	79	86
TPR	85	77	86	73	73	75	78	78	69	78	78	69	86	78	86	81	76	80	88	79	86
F-Measure	85	76	85	71	71	74	78	77	67	78	77	67	86	77	85	80	85	79	88	80	86
ROC	94	84	92	75	75	79	86	86	71	86	86	71	95	85	92	88	82	86	96	87	93
No. of IF	51	51	51	7	7	9	15	25	8	15	25	8	36	26	36	18	18	18	22	22	22

Performance Evaluation of the Proposed VIGAREA With Other Classifiers

With the motivation to check how the proposed VIGAREA is functioning with various classifiers, the performance of various classifiers before and after the application proposed VIGAREA is compared. For comparison most of the classifiers which are already used in the literature for ART related studies are chosen. The same ART dataset maintained by HFEA is taken for the experiment and the results are shown in Table 6.

Table 6. Performance of Various Classifiers Before and After the Application of Proposed VIGAREA.

Classifiers	Performance Metrics											
	Before Proposed VIGAREA						After Proposed VIGAREA					
	Accuracy (%)	ROC Area (%)	F-Measure (%)	PRC Area (%)	MAE	Time Taken (s)	Accuracy (%)	ROC Area (%)	F-Measure (%)	PRC Area (%)	MAE	Time Taken (s)
RF	84.6	93.4	84.6	93.2	0.14	14.3	86.0	93.0	86.0	93.0	0.15	12.40
PART	88.7	89.4	88.4	89.6	0.15	37.7	84.6	89.0	86.0	88.0	0.16	30.70
J48	84.7	83.8	84.0	85.6	0.19	1.23	84.0	86.8	84.0	84.4	0.16	0.48
REP Tree (DT)	83.7	83.7	83.9	85.5	0.20	0.91	82.0	85.8	82.1	84.3	0.15	0.66
K-Star	82.7	92.5	82.1	91.9	0.19	0.02	81.4	93.1	81.4	93.2	0.19	0.01
IB1	85.0	92.3	84.3	91.4	0.15	0.01	86.2	93.3	86.4	93.0	0.14	0.01
A1DE Updatable	77.2	84.4	76.2	84.8	0.26	0.12	79.0	87.0	79.5	87.1	0.21	0.11
Proposed EHIC	85.0	94.1	84.7	94.1	0.15	0.20	87.6	95.5	87.5	95.5	0.13	0.11

The results of Table 6 revealed that most of the classifiers performance is improved after the application of proposed feature ranking algorithm for ROC metric. For some classifiers the performance is slightly reduced, but it is promising that the classifiers achieves this performance with the reduced feature of 22 whereas the original dataset contains 52 features.

When analyzing the results deeply the interesting facts that are identified is actually the threshold limit for the proposed hybrid feature ranking algorithm is set by evaluating its performance with the proposed EHIC. Hence the performance of the ensemble and the performance of the base learner IB1 and A1DE updatable are greatly improved for all the metrics. Whereas for the tree based classifiers the performance improved for ROC metric and reduced slightly for accuracy.

Even though the proposed feature ranking is showing promising performance, its performance can be improved by choosing appropriate feature selection methods for combination. Hence it is recommended that the performance of the classifier can be improved by selecting suitable feature selection methods for that particular classifier and combine those methods using VIGAREA and sets the threshold based on its evaluation.

Comparing the performance of the Proposed EHIC with and without the Proposed Feature Ranking Algorithm

The performance of the EHIC model, before and after applying the proposed feature ranking algorithm, is shown in Figure 4.

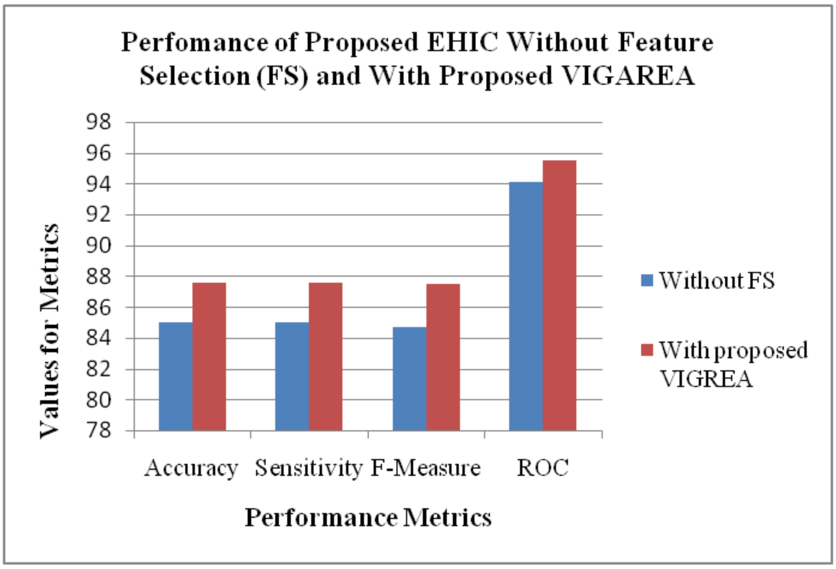

Figure 4. Comparison of Proposed EHIC with and without Proposed Feature Ranking Algorithm.

Figure 4 shows that the performance of the EHIC model has improved after applying the proposed feature ranking method. It underscores the need to find influencing features,and also demonstrates that supplying relevant features enhances the performance of the model. Thus, the experiment has justified the use of the proposed feature ranking algorithm.

Performance Evaluation of the Proposed Model with the Existing State-of-Art Models Used for ART Outcome Prediction

The performance of the proposed model is checked with the existing models available for ART related works. In order to ensure appropriate comparison, all the models are provided with the same ART dataset balanced by SMOTE. The results of the comparison are shown in Table 7.

Table 7. Performance Evaluation of the Proposed Model with the Existing State-of-Art Models Used for ART Outcome Prediction

Reference	Feature Selection	Classifier	No. of Selected Features	Performance Metrics					
				Accuracy (%)	ROC Area (%)	F-Measure (%)	PRC Area (%)	MAE	Time Taken (s)
Durairaj et al., [37]	PSO	NB	27	74.26	80.1	80.7	80.7	0.324	0.01
Vijayalakshmi et al., [38]	CFS	J48	08	72.75	74.3	71.0	74.0	0.366	0.21
Hafiz.P et al., 2017 [39]	Chi- square Ranking	RF	26	86.40	93.7	86.2	93.4	0.196	12.20
Asil Uyar et al., [40]	Forward FS	NB	08	72.00	75.0	70.9	74.8	0.367	0.01
Nanni et al., [41]	SFFS	RSDT	08	71.59	74.9	69.6	74.7	0.414	0.69
Proposed Model	Proposed VIGARE	Proposed EHIC	22	87.60	95.5	87.5	95.5	0.130	0.05

The results of Table 7 make it clear that the performance of the proposed model out beats the other model with the ROC of 95.5 with the selected feature of 22. Next to the proposed model RF with chi-square ranking proposed byHafiz.Pand coauthors (2017) (39) achieves 93.7 ROC value with 26 influencing attributes. The performances of the other models are comparatively low. This experiment makes it plain that the proposed model outperforms the other model in all the metrics and ensures its applicability for ART outcome prediction.

Calculating the Computational Complexity of the Proposed Methods

The computational complexity of the EHIC is calculated based on the time and space complexity of the base learners. The training time taken for the proposed algorithms depends on the number of training example taken and the number of attributes. The time taken for classification depends on the number of classes and the number of attributes. The space complexity of the EHIC depends on the number of training examples, the number of distinct values for each attribute and the number of available classes. The time complexity of the proposed hybrid feature ranking algorithm VIGAREA, depends on the number of FS algorithm chosen for combination as well the running time needed for those methods. The results are shown in Table 8

Table 8. Computational Complexity of the Algorithms

Algorithm	Training		Classification	
	Time	Space	Time	Space
Proposed EHIC	$O(tn^2) + O(ts)$	$Max(O(k(nv^2)), O(s))$	$O(kn^2) + O(s)$	$Max(O(k(nv^2)), O(s))$
Proposed VIGAREA	$O(nf)$	$O(tr)$	-	-

$k$is the number of classes
n is the number of attributes
v is the average number of values for an attribute
t is the number of training examples
s is the number of instances retained in the subset (Concept Descriptor)
$f$is the number of feature selection methods chosen
$r$is the number of reduced attributes

CONCLUSION

In this research work, a novelhybrid feature ranking algorithm based on EHIC for ART outcome prediction is proposed. The feature ranking algorithm is proposed by combining the results of existing feature selection algorithms using voting, and taking into consideration the information gain ratio of individual features. The dynamic ensemble model with the proposed feature selection method achieves the highest prediction with an Area Under the ROC of 95.5 for the HFEA ART dataset. The efficiency of the proposed method is checked with various feature selection methods as well as with various classifiers and it is identified that the proposed feature ranking method performs good. The performance of the proposed model is checked with other models and found that the former is performing better. So it is concluded that the proposed model may be useful for the physicians and biologists worldwide, for ART outcome prediction.

The strength of the proposed hybrid feature ranking algorithm VIGAREA is it can combine any number and type of feature selection methods along with information gain ratio. It has the capability to work in a versatile manner and preserves the importance of a single feature as well as the interdependent performance. The limitation is that the performance of the proposed VIGARE algorithm depends on the feature selection methods that are selected for combination.

Further research can be carried out in the following directions. One of the important factors that influence the success of ART treatment is the embryos transfer. Separate research can be carried out to choose the best embryos and also the number of embryos that can be transferred in a single cycle. This research work takes physical and reproductive fitness factors into consideration. But environmental and social factors may have impact on infertility. Hence environmental and social factors that affect fertility may also be taken into account and can apply associative rule mining to find any common pattern in the data. Further research can be done to predict which fertility treatments is better suited to couples having specific characteristics and to understand how the treatment effect vary with respect to couples' characteristics.

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