

# Classifiers with synthetic oversampling pre-process for In Vitro Fertilization predictions

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## Abstract

Assisted reproductive technology (ART) has been explored extensively to establish the predictive models as one of the automated tool to measure the for-IVF quality outcomes depending on the Age, Anti-Müllerian hormone (AMH), Right ovary (RO), Left Ovary (LO), Number of eggs, No of Insemination, no of fertilized, Egg quality attributes. Artificial Intelligence (AI) field has connectionism based Artificial Neural Networks and they are capable of supporting the classification or estimation needed. Research community has been working with shallow and deep learners as part of machine learning and contributing improved results by combining various models and trying different frameworks for similar types of problems. In this article supervised learning is applied for training and testing the IVF dataset with limitations such as small data size and imbalanced class distribution. It is achieved with the set of selected classifiers and appropriate filters in the pre-processing, a weighted ROC score 84% and accuracy 75%.

## Keywords

Supervised models, In vitro fertilization (IVF), Synthetic Minority Oversampling Technique (SMOTE) Filter, Anti-Müllerian hormone (AMH), Antral Follicle Count (AFC)

## 1. Introduction

It is observed that decision support systems for medical domain especially in reproductive assisting systems are available in plenty which are based on artificial neural networks. However, such systems for predictions in IVF domain are relatively less.

Over fitting or lack of generalization in artificial neural networks induces instability in them. Moreover, the easier traps for local minima made difficult to use them as predictive tools. The degree of complexity of such inherent problems is considerably reduced by other types of models as current researchers often propose and get improved performance. In this article we mainly consider supervised learning models [1,2] such as J48, Random Forest, JRip, Decision table, IBK, Kstar, SMO, Multilayer perceptron, Naïve Bayes, Bayes net, Adaboost and Bagging.

Among many serum markers Anti-Müllerian hormone (AMH) is a standard one for applying as an ovarian retrieved test (Wunderet al., 2008). Serum AMH level reveals the total granulosa amount seen as the pool of follicular [18]. The serum level in AMH of less than 80% per milliliter, with additionally FSH greater than 10 IU/mL were considered as risky situation for worse ovarian outcome as it is directly proportional with increasing age.

AMH assay were adopted as the first line OR test. A review had been done (Wiwekoet al., 2013) for associating biological and biological age based on nomograms taken with markers like FSH, AMH, and AFC. Earlier research work of similar type shows the tight association between the frequency of present pregnancy in very first embryo transfer iterations and AMH reflecting the sum of all AMH producing follicles [19]. There are other retrospective studies are available where one can find the connection of clinical factors like patient maturity, levels of AMH, inhibin B, FSH, AFC, and the frequency of retrieved oocytes to predicting the success rate of live birth for women who were treated in vitro fertilization[12].

Analyzing statistically showed that the probabilities of live birth expressively reduced with growing age, deteriorating concentrations of AMH or inhibin B, finally with smaller retrieved oocytes. At higher levels it is observed that in AMH levels increases the complexity of live birth when they were lower levels [20]. The presence of statistical significance of the markers AMH, AFC associated with live birth is supporting forecasts for IVF patients (Bas Landoet al., 2017).

Another prospective research executed on patients experiencing their IVF test for the first time [21], shown that AMH is a hopeful bio marker indicating the ovarian response prediction and that with a cutoff value 2.97 ng/mL that can be implemented for this prediction (Kotanidiset al., 2016).

Conferring to the data of an examination, a poor response to ovarian stimulus can be expected with the aid of AFC [22] (Muttu Krishna et al., 2005). The study by Hendriks et al. (2005) observed the role of AFC is deprived in predicting to achieve pregnancy and suggest that AFC regulates only the oocyte number, but clinically appropriate pregnancy outcome or live birth based on the quality and quantity of oocyte[23].

The algorithm for supervised learning applied to a dataset of such IVF cases learns a model that can be represented and tested for probable estimate or the likelihood of success [4]. The desired output and the actual network output are compared and the result shows the most perfect output and aim the success rate of IVF treatment using ANN (Durai raj et al 2013).

Data mining techniques in particular decision tress were used to establish the mapping the attributes like follicle embryo, and oocyte to the possible success in outcome of the embryo transfer [13]. They could achieve with an accuracy up to 67.4% using decision tree induced based on c5.0 attribute winnowing algorithm. (Passmore et al. 2013).

The algorithms like naïve bayes classifier with 80.4 % accuracy, 67.7 sensitivity and false alarm rate in embryo based implantationprediction, ranking algorithm roc curve with 75 % accuracy proposed SERA[8] algorithm was also applied successfully for the estimation of the probability of success in IVF treatment ( Guvenir et al. uyar et al).

In the following sections the proof for establishing proposed claim is demonstrated: section 1 describes relevant references as related works for this proposed hypothesis, section 2 makes improving the readability by presenting materials and methods, section 3 covers the data collection and description, section 4 elaborates the proposed method, section 5 presents the presents the experimental set up and results prescribed with the future remarks in conclusion.

## **2.Materials and Methods**

### **2.1. ART characteristics**

In Vitro fertilization, a method of ART is the merging of women-egg and man- spermatozoid external to the body. An IVF treatment phase [3,5,6] having the attributes like pituitary down regulation, controlled ovarian stimulation, oocytes recovery, in vitro fertilization of eggs with sperm, transfer of resulting embryos back to uterus, and luteal phase support. Stopping LH surge during limited ovarian stimulation is achieved by pituitary down regulations using measures of ‘gonadotrophin’ releasing agonist which is generally recognized as agonist cycle [7,9]; IVF cycle studies include two meta-analyses that have established the association of AFC to deprived ovarian response to stimulate gonadotropin. This AFC might aid along counselling and selection of suitable treatment procedures and dosing schedule as AFC relates to the quantity of allotted follicles and recovered oocytes. There are only few examinations that recommends AFC which is functional in forecasting autologous IVF cycle pregnancy results. Conferring to some reports; clinical pregnancy, lower pregnancy, and live birth rates are observed in women with the status AFC below 10 OR refers to the functional prospective of the ovary that institutes the size of the ovarian follicle pool and redirects the quality and quantity of oocytes within it. OR assessment helps in replicating the reproductive prospective of women. Numerous markers are accessible for OR assessment and the best among them is AMH which imitates the ovarian follicular pool in the ovary [14,15].

Assisted reproductive technique gives childless couples to have baby and different technique like in vitro fertilization, intracytoplasmic sperm jab, pre implantation at genetic diagnosis, gamete and embryocryo preservation are used now days for treatment options to achieve greater rate of success. As the above treatment is very higher chance of success rate by using patient’s parameters contribute to a great advantage in the field of reproductive medicine [10,11]. The various techniques in machine learning, data mining technique and statistical approached can be used to analyse a clinical database to predict the success in IVF outcome. The patient characteristics were used as set of attributes to predict the outcome and the models learned by these techniques are to be employed for assisting the physicians to estimate the probability of success for an infertile patient [16,17].

### **2.2 Filter and Classifiers**

SMOTE: Synthetic Minority Oversampling Technique (SMOTE) common strategies for dealing with unbalanced class in classification problems. SMOTE is an oversampling technique where the synthetic samples are generated for the minority class. If the unbalanced data is not taken care beforehand which may degrade the performance of the classifier model. Most of the prediction will be made with majority class wherein the minority will be treated

as noise and disturbance and will be ignored by the classifier algorithm resulting in a high bias in the model. The effect of 'SMOTE' clearly shows that uniform increment in the selected classifiers.

Selected Classifiers: J48, a decision tree model, having branches with significant attributes selected by entropy measures and it is conventionally used, derived from traditional algorithms ID3, C4.5. Though it is easily interpretable the complexity is relatively higher comparing to other similar algorithms like decision rules or instance-based algorithms. The ensemble classifiers are selected namely Random Forest, Adaboost, bagging as the performance is by majority of member classifiers in the committee of model. Instance based classifiers Kstar and IBk are selected as they are very simple to be interpreted, The SMO, Multi-Layer perceptron for linear separation like model at the hyper space is being generated, and Probability measures with independent events assumption are produced by Naïve, Bayes.

### 3.Data set description:

After the approval from institutional review board, this study was conducted for analysis of data gathered from the Prashanth fertility IVF center. The study material includes around 300 women who was undergoing their first cycles in vitro fertilization treatment between year 2016 -2018.

Inclusion criteria to be considered for valid instance are the following: a) Observing regular pattern in menstrual cycle; b)Not allowing any hormone therapy for three months : c) Not having any surgical operation inside the reproductive system.

Exclusion criteria are the following:

- Women with endometriosis, PCOS, history of ovarian surgery or endocrine disorders were excluded from the study.
- The ovarian stimulation was achieved by monitoring 150 IU/day of recombinant FSH 100 IU/day (Recagon ) under pituitary suppression with a Gn RH agonist according to the ovarian responses which is assessed by TVS scan and serum estradiol measurement. The oocytes were aspirated 34 – 36 h after hCG injection and intra cytoplasmic sperm injection was carried out using standard methods.
- The retrieved oocytes with quality oocytes were considered as study endpoints. The clinical pregnancy was confirmed by the presence of sac for gestation or by biochemically pregnancy was defined by the presence of b- HCG greater than 50 mIU/ml. Clinical details of all treatment cycles were entered and the database was accessed for analysis. Embryo transfer were performed under abdominal cross section scan using a soft tube insertion and finally determination of pregnant state was confirmed (urine test, ultrasound test, later to confirm intrauterine pregnancy and the presence of sac for gestation.

To avoid the class imbalance in our dataset which contains originally 327 having class distribution:118 negative,209 positive instances. We are applying SMOTE filter which preserves the attribute dependence property as well as with the reduced imbalance as class distribution 212 negative,208 positive instances.

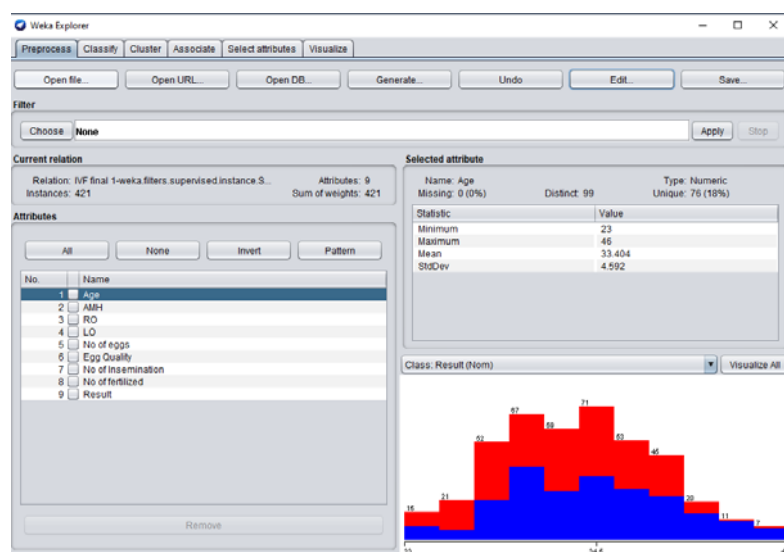


Fig.1 Attribute list with the range in the WEKA screen shot

The above screen shot lists the eight attributes namely Age, Anti-Müllerian hormone (AMH), Right ovary (RO), Left Ovary (LO), Number of eggs, No of Insemination, no of fertilized, and Egg quality.

#### 4. Proposed Method:

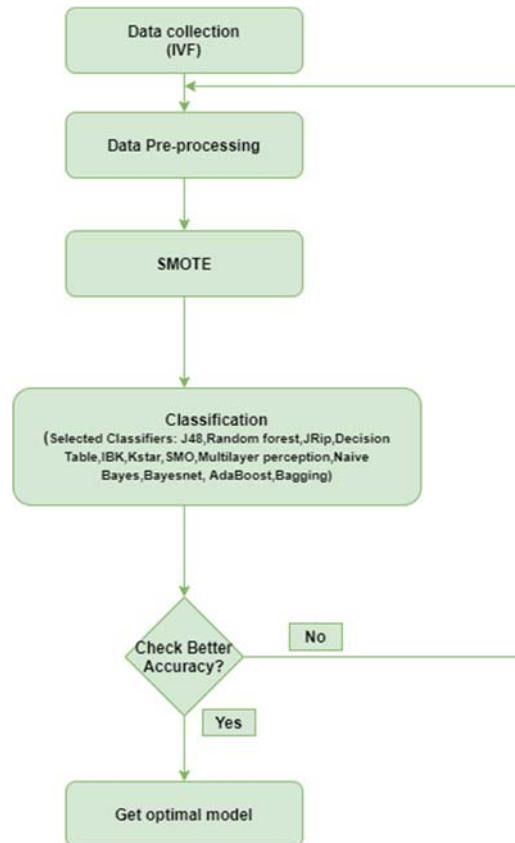


Fig.2 Proposed method for mining the IVF dataset.

Data on IVF instances are collected as mention in section 3. Firstly, the redundancy or insignificant labels are stream lined along removing the ranks dominating the attribute values as data pre-processing. Secondly smote filter is applied for the reasons as mention in section 2. Then it is followed by training and testing with the classifiers J48, Random Forest, JRip, Decision table, IBK, Kstar, SMO, Multilayer perceptron, Naïve Bayes, Bayes net, Adaboost and Bagging.

## 5. Experiment Results and Discussion

Table 1: performance measure for selected classifiers

S.No	Category	classifier	Correctly Classified Instances (%)	Weg. Average ROC	Weg. Average Precision	Weg. Average Recall	Weg. Average F-Measure
1.	Trees	J48	68.8836 %	0.682	0.697	0.689	0.685
2.	Trees	Random Forest	74.5843 %	0.819	0.746	0.746	0.746
3.	Rules	JRip	64.133 %	0.666	0.643	0.641	0.640
4.	Rules	Decision Table	67.9335 %	0.694	0.695	0.679	0.672
5.	Lazy	IBK	71.734 %	0.714	0.721	0.717	0.716
6.	Lazy	K star	75.0594 %	0.842	0.765	0.751	0.747
7.	Function.	SMO	61.7577 %	0.617	0.624	0.618	0.612
8.	Function.	Multilayer perceptron	68.4086 %	0.708	0.684	0.684	0.684
9.	Bayes	Naïve Bayes	64.8456 %	0.681	0.665	0.648	0.639
10.	Bayes	Bayesnet	65.7957 %	0.682	0.667	0.658	0.653
11.	Meta	AdaBoost	65.0831 %	0.701	0.656	0.651	0.647
12.	Meta	Bagging	71.2589 %	0.770	0.713	0.713	0.713

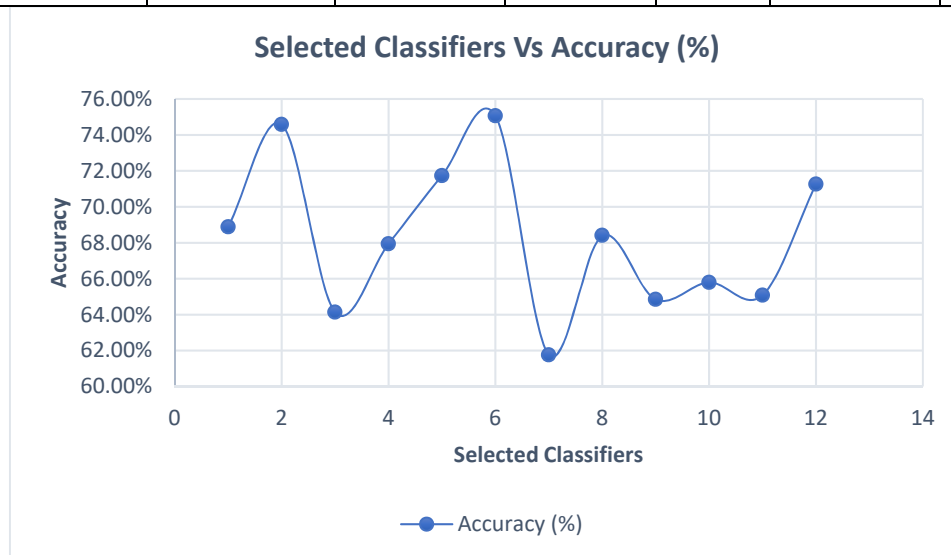


Fig. 3 Selected Classifiers Vs Accuracy

K star Classifier obtains maximum accuracy 75.0594 % whereas SVM classifier yields minimum accuracy performance 61.7577 % in the family of selected classifiers in our proposed iterations.



Fig. 4 Selected Classifiers Vs Weg. Average ROC

K star Classifier obtains maximum weighted. average ROC 0.842 whereas SVM classifier yields minimum weighted average ROC 0.617 in the family of selected classifiers in our proposed iterations

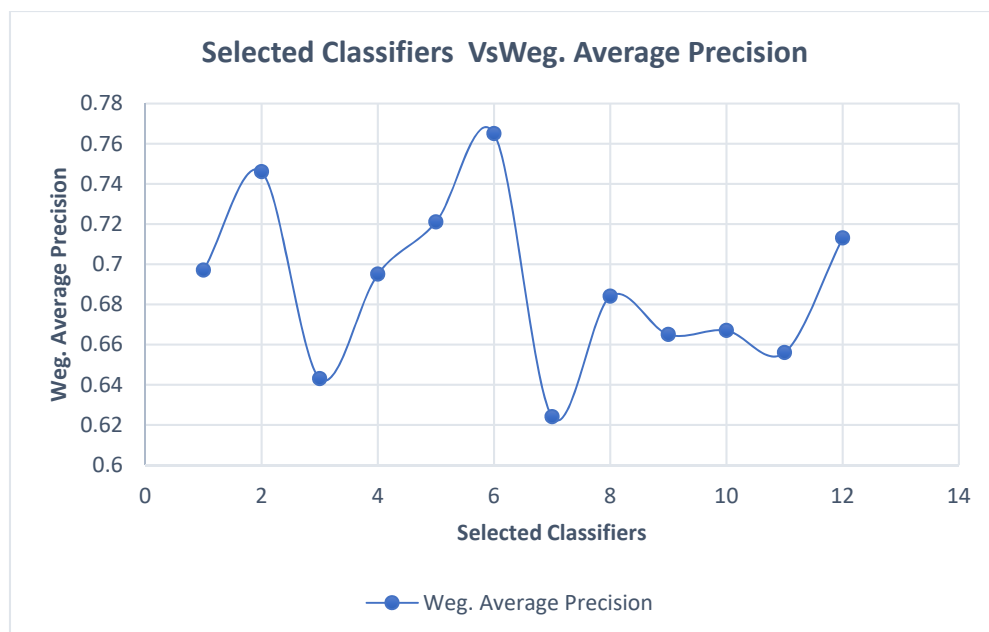


Fig.5 Selected Classifiers Vs Weg. Average Precision

K star Classifier obtains maximum weighted. average Precision 0.765 whereas SVM classifier yields minimum weighted average Precision 0.624 in the family of selected classifiers in our proposed iterations

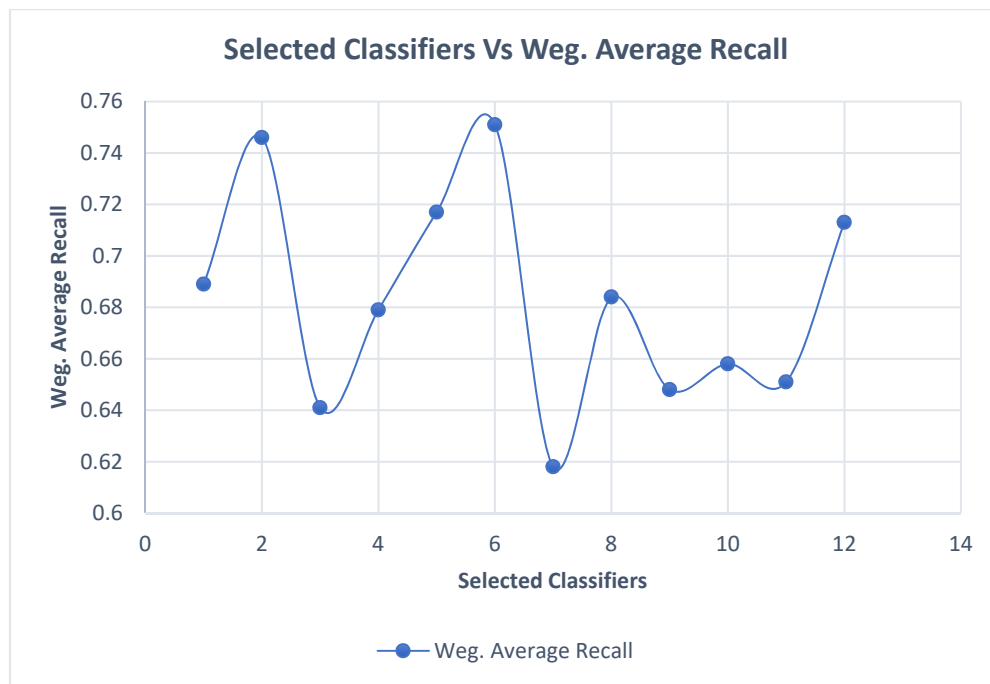


Fig. 6 Selected Classifiers Vs Weg. Average Recall

K star Classifier obtains maximum weighted. average Recall 0.751 whereas SVM classifier yields minimum weighted average Recall 0.618 in the family of selected classifiers in our proposed iterations.

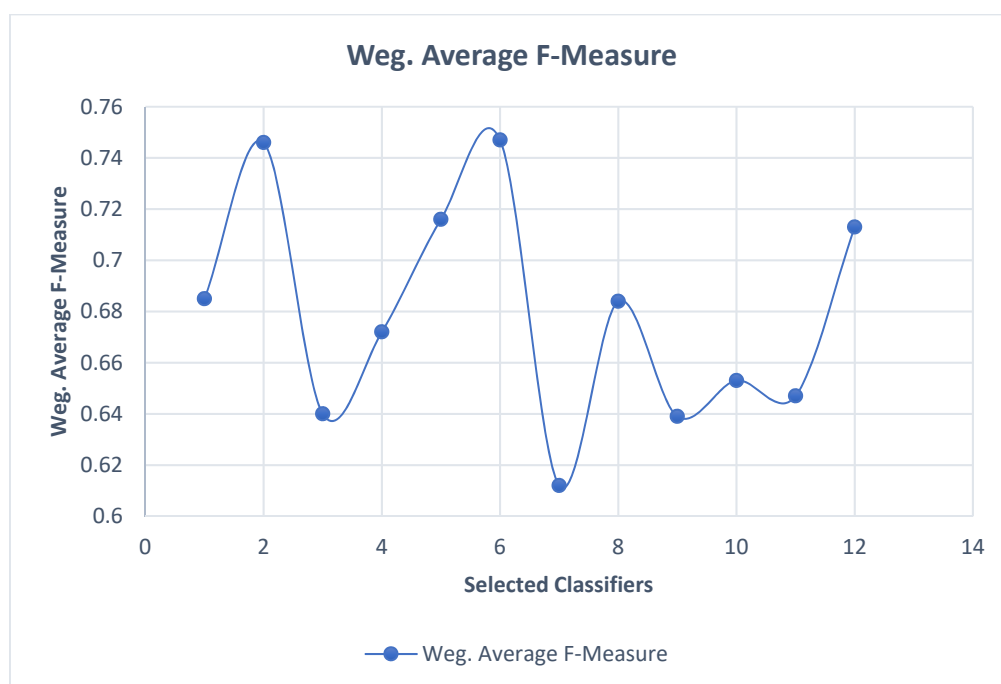


Fig. 7 Selected Classifiers Vs Weg. Average F-Measure

K star Classifier obtains maximum weighted. average F-Measure 0.747 whereas SVM classifier yields minimum weighted average F-Measure 0.612 in the family of selected classifiers in our proposed iterations.

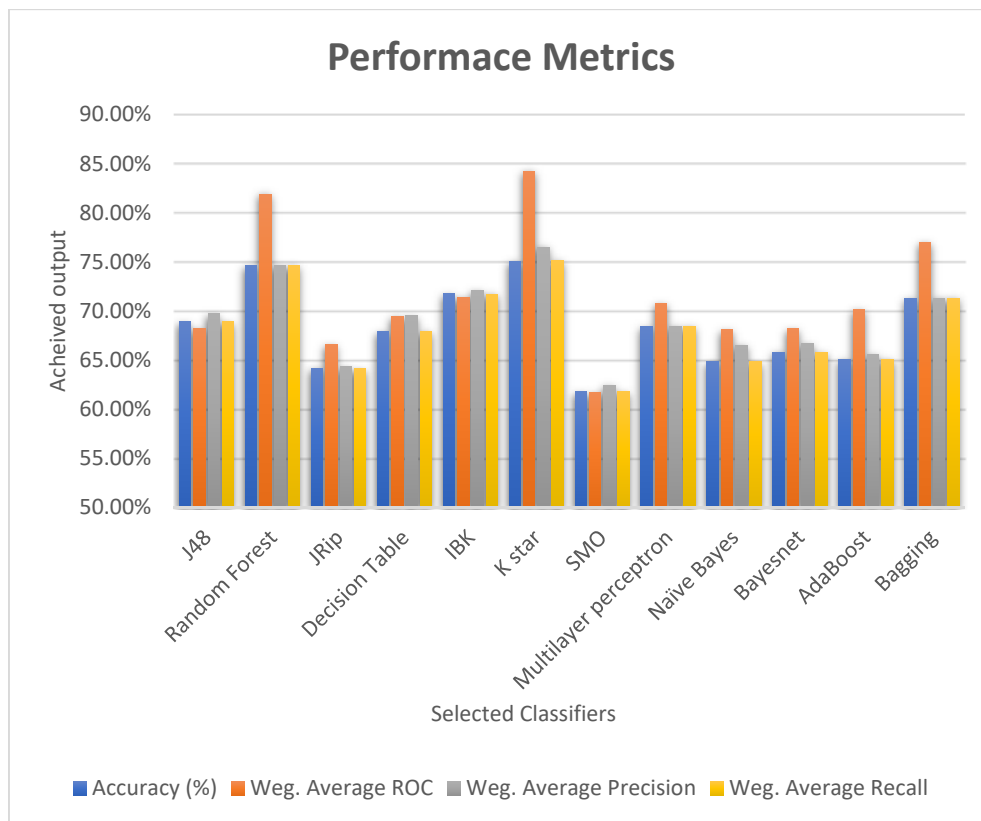


Fig.8 Selected Classifiers Vs Output parameters

The above figure clearly shows the ensemble family of classifiers like Bagging, Adaboost give not much performance. in the same way SVM, Decision Rules, Decision Trees learners exhibit lower performance.

## 6. Conclusion

The proposed methodology yields a maximum of Weighted average ROC of 84% and 75% accuracy. Among the selected classifiers discussed in the experiment set up, the instance based K\* and random forest contributes to such a result. It is also observed that the SMOTE filter supports the result without the interference of instability due to imbalanced class distribution. In future iterations with number of folds in cross validations and more classifiers' parameter tuning can be considered so that such relational data sets can be made stronger than any possible image sets for IVF treatments for predicting the quality outcomes.

## Statement on No conflict of interest:

There is no conflict of interest among the Authors of this Article.

## References

- [1] Balogun, J.A., Egejuru, N.C., & Idowu, P. A. (2018): Comparative Analysis of Predictive Models for the Likelihood of Infertility in Women Using Supervised Machine Learning Techniques. *Computer Reviews Journal*, 2, pp.313–330.
- [2] Hassan, M. R., Al-Insaif, S., Hossain, M.I., & Kamruzzaman, J. (2018): A machine learning approach for prediction of pregnancy outcome following IVF treatment. *Neural Computing and Applications*, pp.1-15.
- [3] Demyttenaere K, Bonte L, Gheldof M, Vervaeke M, Meuleman C, Vanderschuerem D, D'Hooghe T (1998): Coping style and depression level influence outcome in in vitro fertilization. *Fertility and Sterility* 69(6): pp.1026-1033
- [4] Durairaj M, Thamil selvan P (2013): Applications of artificial neural network for IVF data analysis and prediction. *Journal of Engineering, Computers and Applied Sciences* 2(9), pp. 11-15
- [5] Durairaj M, Nandhakumar R (2014): An integrated methodology of artificial neural network and rough set theory for analyzing IVF data. In: 2014 International Conference on Intelligent Computing Applications (ICICA), pp 126-129.
- [6] Fayyad U, Usama, Piatetsky-Shapiro G, Smyth P (1996): The KDD process for extracting useful knowledge from volumes of data. *Communications of the ACM*, 39(11), pp.27-34.
- [7] Guh R, Wu TCJ, Weng SP (2011): Integrating genetic algorithm and decision tree learning for assistance in predicting in vitro fertilization outcomes. *Expert Systems with Applications*, 38(4), pp.4437-4449.
- [8] Guvenir HA, Misirli G, Dilbaz S, Ozdegirmenci O, Demir B, Dilbaz B (2015): Estimating the chance of success in IVF treatment using a ranking algorithm. *Medical & Biological Engineering and Computing*, 53(9), pp.911-920.
- [9] Hafiz P, Nematollahi M, Boostani R, Bahia NJ (2017): Predicting implantation outcome of In Vitro fertilization and intracytoplasmic sperm injection using data mining techniques. *Fertility and Sterility*, 11(3), pp.184-190.
- [10] Uyar A, Bener A, Ciray HN, Bahceci M (2010): ROC based evaluation and comparison of classifiers for IVF implantation prediction. *Electronic Healthcare*, pp. 108-111.



- [11] Uyar A, Ayse B, Ciray HN (2015): Predictive modelling of implantation outcome in an in vitro fertilization setting: an application of machine learning methods. *Medical Decision Making* 35(6): 714-725.
- [12] Jurisica I, Mylopoulos J, Glasgow J, Shapiro H, Casper RF (1998): Case-based reasoning in IVF: prediction and knowledge mining. *Artif Intel in Med*.12(1), pp.1–24.
- [13] Passmore, L., Goodside, J., Hamel, L., Gonzalez, L., Silberstein, T., Trimarchi, J (2013): Assessing decision tree models for clinical in-vitro fertilization data. Technical report, Dept. of Computer Science and Statistics University of Rhode Island.
- [14] Trimarchi, J.R., Goodside, J., Passmore, L., Silberstein, T., Hamel, L., Gonzalez, L (2003): Comparing data mining and logistic regression for predicting Ivf outcome. *Fertil. Steril.*
- [15] Morales, D.A., Bengoetxea, E., Larranaga, B., Garcia, M., Franco, Y., Fresnada, M., Merino, M(2008): Bayesian classification for the selection of in vitro human embryos using morphological and clinical data. *Computer Methods and Programs in Biomedicine*, 90, pp.104–116
- [16] Broer SL, Dolleman M, Opmeer BC, Fauser B, Mol BW, Broekmans F J (2011): AMH and AFC as predictors of excessive response in controlled ovarian hyperstimulation: a meta-analysis. *Hum Re prod Update.* 17(1), pp.46–54.
- [17] Dhillon RK, Mc Leron DJ, Smith PP, Fishel S, Dowell K, Deeks JJ, et al. (2016): Predicting the chance of live birth for women undergoing IVF: a novel pre-treatment counselling tool. *Human Reproduction*,31, pp.84–92. doi: 10.1093/humrep/dev268.
- [18] Wunder DM, Bersinger NA, Yared M, Kretschmer R, Birkhäuser MH (2008): Statistically significant changes of antimüllerian hormone and inhibin levels during the physiologic menstrual cycle in reproductive age women. *Fertil Steril.* 89(4), pp.927-33. doi: 10.1016/j.fertnstert.2007.04.054. Epub 2007 Jul 2. PMID: 17603052.
- [19] Wiweko B, Prawesti DM, Hestiantoro A, Sumapraja K, Natadisastra M, Baziad A (2013): Chronological age vs biological age: an age-related normogram for antral follicle count, FSH and anti-Müllerian hormone. *J Assist Reprod Genet.* 30(12): pp.1563-1567.
- [20] Bas-Lando M, Rabinowitz R, Farkash R, Algur N, Rubinstein E, Schonberger O, Eldar-Geva T (2017): Prediction value of anti-Müllerian hormone (AMH) serum levels and antral follicle count (AFC) in hormonal contraceptive (HC) users and non-HC users undergoing IVF-PGD treatment. *Gynecol Endocrinol*,33(10), pp. 797-800. doi: 10.1080/09513590.2017.1320376.
- [21] Kotanidis, Lazaros,AU - Konstantinos, Nikolettos,(2016) :The use of serum anti-Müllerian hormone (AMH) levels and antral follicle count (AFC) to predict the number of oocytes collected and availability of embryos for cryopreservation in IVF, Vol. 39, *Journal of Endocrinological Investigation*, .DOI:10.1007/s40618-016-0521,
- [22] Muttukrishna S, McGarrigle H, Wakim R, Khadum I, Ranieri DM, Serhal P(2005):Antral follicle count, anti-müllerian hormone and inhibin B: predictors of ovarian response in assisted reproductive technology? *BJOG.* 2005 Oct;112(10), pp.1384-90. doi: 10.1111/j.1471-0528.2005.00670. x. PMID: 16167941.
- [23] Hendriks DJ, Mol BW, Bancsi LF, Te Velde ER, Broekmans FJ (2005): Antral follicle count in the prediction of poor ovarian response and pregnancy after in vitro fertilization: a meta-analysis and comparison with basal follicle-stimulating hormone level. *FertilSteril.* 2005 Feb;83(2), pp.291-301. doi: 10.1016/j.fertnstert.2004.10.011. PMID: 15705365.

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