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# Secondary Testosterone Deficiency Identification Using Machine Learning Classifier

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**ABSTARCT:** The most significant hormone involved in male sex, testosterone deprivation has numerous negative effects on the body and mind. Identifying low testosterone patients effectively is essential before initiating appropriate treatment. However, routine testosterone level monitoring can be expensive in many places, which leads to a case-reporting underreporting, particularly in developing nations. Furthermore, not many studies use machine learning (ML) to predict testosterone deprivation. The aims of the paper to Secondary testosterone deficiency (STD) poses significant health risks and necessitates accurate prediction for timely intervention. In this study, (1) we address the challenge of STD prediction by leveraging machine learning (ML) techniques. (2) Building upon existing research employing diverse sampling technologies and classifiers, (3) we propose a novel approach integrating Synthetic Minority Over-sampling Technique (SMOTE) sampling and XG Boost classifier. Our methodology involves stratified 10-fold cross-validation to ensure robust model evaluation. (4) Compared to prior efforts achieving an average accuracy of 80%, our proposed system attains an improved accuracy of 96%. Further research and validation on larger and more diverse datasets are warranted to validate the generalizability and scalability of our approach. Overall, our study contributes to addressing the critical need for accurate prediction of testosterone deprivation, thereby mitigating its negative health impacts .

**KEYWORD:** Testosterone deficiency prediction, Machine learning, Synthetic Minority Over-sampling Technique (SMOTE), XG Boost classifier, Secondary testosterone deficiency (STD), 10-fold cross-validation.

## I. INTRODUCTION

Testosterone, the primary sex hormone in men, has a substantial impact on both their physical and mental health. Patients with Testosterone Deficiency Syndrome (TDS) may develop hypogonadism, characterized by low serum testosterone levels and clinical symptoms. Comorbidities connected with this disorder include metabolic syndrome, cardiovascular diseases, erectile dysfunction, atherosclerosis, respiratory issues, depression, and other difficulties that negatively impact overall health.

Secondary testosterone shortage is caused by an issue with the pituitary gland or hypothalamus, resulting in insufficient testosterone production. The assignment required researching various publications and developing a proposed machine learning model. To address the imbalance in the dataset, three sampling strategies were used: under-sampling, over-sampling, and hybrid-sampling. Over-sampling can be random or systematic.

Secondary hypogonadism has therapeutic implications. It may be treatable or preventable by treating or preventing functional reasons (such as obesity, type 2 diabetes, opioids, or systemic disease). Male hypogonadism and obesity are related, according to a number of reviews and meta-analyses. According to studies, obese men who lose weight by controlled exercise, nutrition, or, in more extreme situations, bariatric surgery, may see a rise in testosterone levels. Additional therapies include testosterone gel supplementation or hormone replacement therapy, where testosterone treatment decreased waist circumference and visceral obesity. All things considered, several research have demonstrated that weight reduction might result from elevated testosterone levels and vice versa

## II. LITERATURE SURVEY

Quan Zou [2] et al. discussed in this study, we used decision tree, random forest and neural network to predict diabetes mellitus. The dataset is the hospital physical examination data in Luzhou, China. It contains 14 attributes. In this study, five-fold cross validation was used to examine the models. In order to verify the universal applicability of the methods, we chose some methods that have the better performance to conduct independent test experiments. We randomly selected 68994 healthy people and diabetic patients' data, respectively as training set. Due to the data unbalance, we randomly extracted 5 times data. The results showed that prediction with random forest could reach the highest accuracy ( $ACC = 0.8084$ ) when all the attributes were used.

Pei-Ling Chen [3] et al. discussed in the diagnosis of late-onset hypogonadism (LOH), the Androgen Deficiency in the Aging Male (ADAM) questionnaire or Aging Males' Symptoms (AMS) scale can be used to assess related symptoms. Subsequently, blood tests are used to measure serum testosterone levels. However, results obtained using ADAM and AMS have revealed no significant correlations between ADAM and AMS scores and LOH, and the rate of misclassification is high. Recently, many studies have reported significant associations between clinical conditions such as the metabolic syndrome, obesity, lower urinary tract symptoms, and LOH. In this study, we sampled 772 clinical cases of men who completed both a health checkup and two questionnaires (ADAM and AMS). The data were obtained from the largest medical centre in Taiwan. Two well-known classification techniques, the decision tree (DT) and logistic regression, were used to construct LOH prediction models on the basis of the aforementioned features. The results indicate that although the sensitivity of ADAM is the highest (0.878), it has the lowest specificity (0.099), which implies that ADAM overestimates LOH occurrence. In addition, DT combined with the AdaBoost technique (AdaBoost DT) has the second highest sensitivity (0.861) and specificity (0.842), resulting in having the best accuracy (0.851) among all classifiers. AdaBoost DT can provide robust predictions that will aid clinical decisions and can help medical staff in accurately assessing the possibilities of LOH occurrence.

Meryem Amar [7] et al. discussed, Taking care of the health of people is one of the challenging tasks in the world. Cardiovascular disease is one of the main factors that increase mortality. In order to detect this heart defect, it would be necessary to look for a system able to predict its existence and prevent heart diseases that continues to drastically increase. In this paper, we improved the quality of cardiovascular disease prediction using a better preprocessing phase. It helps in identifying a heart disease of a patient and guide a doctor to better diagnose whether a person has cardiovascular disease or not. To prove our results, we have done a comparison between different Machine Learning algorithms using accuracy, precision, f1-score and recall performance metrics.

Amin Ul Haq [8] et al. discussed in the system is developed based on classification algorithms includes Support vector machine, Logistic regression, Artificial neural network, K-nearest neighbour, Naïve bays, and Decision tree while standard features selection algorithms have been used such as Relief, Minimal redundancy maximal relevance, Least absolute shrinkage selection operator and Local learning for removing irrelevant and redundant features. We also proposed novel fast conditional mutual information feature selection algorithm to solve feature selection problem. The features selection algorithms are used for features selection to increase the classification accuracy and reduce the execution time of classification system. Furthermore, the leave one subject out cross-validation method has been used for learning the best practices of model assessment and for hyperparameter tuning. The performance measuring metrics are used for assessment of the performances of the classifiers. The performances of the classifiers have been checked on the selected features as selected by features selection algorithms. The experimental results show that the proposed feature selection algorithm (FCMIM) is feasible with classifier support vector machine for designing a high-level intelligent system to identify heart disease.

D M Kelly [13] et al. discussed, Testosterone is a key hormone in the pathology of metabolic diseases such as obesity. Low testosterone levels are associated with increased fat mass (particularly central adiposity) and reduced lean mass in males. These morphological features are linked to metabolic dysfunction, and testosterone deficiency is associated with energy imbalance, impaired glucose control, reduced insulin sensitivity and dyslipidaemia. A bidirectional relationship between testosterone and obesity underpins this association indicated by the hypogonadal-obesity cycle and evidence weight loss can lead to increased testosterone levels. Androgenic effects on enzymatic pathways of fatty acid metabolism, glucose control and energy utilization are apparent and often tissue specific with differential effects noted in different regional fat depots, muscle and liver to potentially explain the mechanisms of testosterone action. Testosterone replacement therapy demonstrates beneficial effects on measures of obesity that are



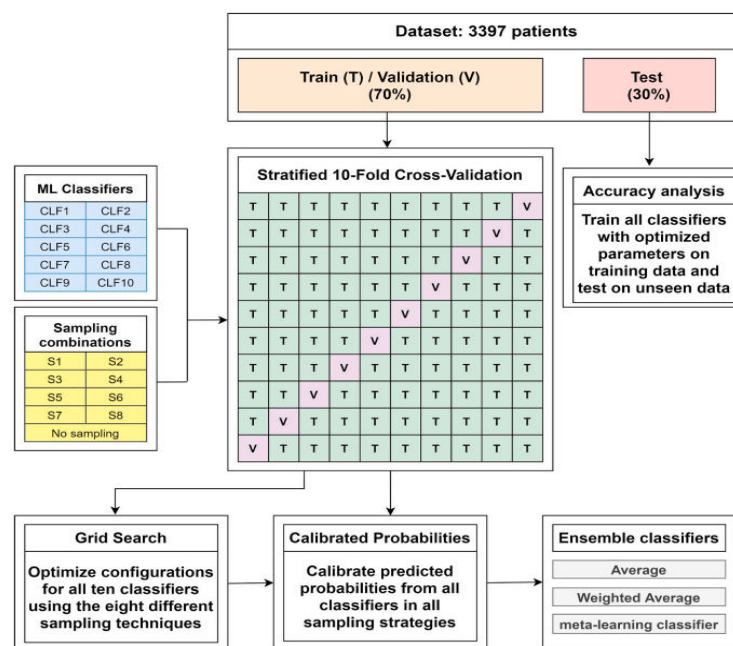
partially explained by both direct metabolic actions on adipose and muscle and also potentially by increasing motivation, vigour and energy allowing obese individuals to engage in more active lifestyles. The degree of these beneficial effects may be dependent on the treatment modality with longer term administration often achieving greater improvements. Testosterone replacement may therefore potentially be an effective adjunctive treatment for weight management in obese men with concomitant hypogonadism.

Steven Lamm [16] et al. The relationship between obesity and hypogonadism is complicated. The relationship is bidirectional and there are numerous causative and correlative factors on both sides of the equation. Obesity is increasing in prevalence in epidemic proportions. Likewise, we are beginning to see the rapid increase in the incidence of male hypogonadism. It is only recently that we are learning the ways in which these 2 conditions exacerbate each other, and we are only beginning to understand how by treating one of these conditions, we can help to treat the other as well.

### III. RESEARCH METHODOLOGY

Implementing Sampling techniques to get balanced data. Here the used sampling techniques are: Synthetic Minority Over-sampling Technique (SMOTE)---Implementing Xg Boost model along with stratified k fold cross validation and hyperparameter tuning using random search to get more accuracy. Using Xg Boost Model finding the deficiency percentage and abnormality level only for the patient which has testosterone deficiency. Generates into new Dataset Finding the level of abnormality.

Our study included 3397 patients aged 40-85 from a urological clinic in Feira de Santana, Brazil. The analysis excluded those who had primary hypogonadism or were undergoing treatment. Low-cost regular tests were used to acquire features such as age, diabetes, HT, HDL, and AC. TG had the largest standard deviation (88.84). HAS and diabetes are categorical characteristics, either absent (0) or present (1). The medical literature indicates that normal testosterone levels. Ensemble classifiers outperform solo classifiers by leveraging their strengths to create a more complicated and effective learning technique. Ensemble predictions use base classifiers' probability outputs to forecast additional data. There are various ensemble procedures, including average (Avg), weighted average (wAvg), majority voting, rank average, and stacking with learning algorithms. This study utilized three ensemble classifiers: Average, wAvg, and Stacking Meta-Classifier using Logistic Regression (meta-classifier). The Average classifier calculates the final probability by averaging the probabilities of all classifiers, making it the most straightforward option. The wAvg algorithm prioritizes superior classifiers. Choosing the optimal set of weights for an ensemble classifier can be a lengthy process.



### Existing Architecture

Datasets are imbalanced when the distribution of classes is uneven [101], and they are prevalent in real-world problems covering many scientific fields [102,103]. ML algorithms often present bad classification results in imbalanced data. There are many ways to address class-imbalance [104]. At the data level, there are three main sampling methods: (a) under sampling (reduction of samples from the majority class), (b) oversampling (enlargement of samples from the minority class), and (c) hybrid sampling (a combination of oversampling and under sampling) [105]. This research compared eight sampling strategy combinations using the open-source python toolbox Imbalanced-Learn [106]: Random under sampling (RUS), Repeated Edited Nearest Neighbours (RENN), Random Over-Sampling (ROS), Synthetic Minority Over-sampling Technique (SMOTE), RENN + SMOTE, RUS + ROS, RENN + RUS, and RUS + SMOTE. RUS is the most straightforward approach.

### IV. EXISTING METHOD

In this research, they aim to offer a coherent comparative analysis of machine learning methods that can predict testosterone deficiency without having patients undergo costly medical tests. In this analysis, we used ten base classifiers (optimized with grid search stratified K-fold cross-validation); three ensemble methods; and eight sampling strategies to analyze a total of 3397 patients. The analysis was based on six features (age; abdominal circumference; triglycerides; high-density lipoprotein; diabetes; and hypertension), all of which were obtained by low-cost exam. Implementing Sampling techniques to get balanced data.

Here the used sampling techniques are:

- Random under sampling (RUS),
- Repeated Edited Nearest Neighbours (RENN),
- Random Over-Sampling (ROS),
- Synthetic Minority Over-sampling Technique (SMOTE)

#### RANDOM UNDER SAMPLING (RUS)

- Random under sampling is a simple under sampling technique in which instances are randomly selected and removed from the majority class until the number of instances in both classes is roughly the same. This technique can be effective when the majority class has a significantly larger number of instances than the minority class. Random under sampling can be a fast and effective way to balance an imbalanced dataset. However, it can also result in the loss of important information and reduce the diversity of the data. As a result, it is important to carefully consider the implications of using random under sampling and evaluate its effectiveness in the context of the specific problem and dataset being analyzed
- Output:

Total rows in balanced dataset: 1066  
Affected rows in balanced dataset: 533  
Unaffected rows in balanced dataset: 533

#### REPEATED EDITED NEAREST NEIGHBORS (RENN)

- RENN (Repeated Edited Nearest Neighbour) sampling is a data preprocessing technique used in machine learning to balance imbalanced datasets. RENN is an extension of the Edited Nearest Neighbour (ENN) algorithm that iteratively removes noisy instances from the majority class until a balanced dataset is achieved. The RENN

algorithm works in two steps. In the first step, the ENN algorithm is applied to remove noisy instances from the majority class. ENN removes an instance from the majority class if its class label differs from the class label of its k-nearest neighbours. The k parameter is a user-defined parameter that controls the level of sensitivity to noise. After applying the ENN algorithm, the majority class is reduced to a smaller subset of instances that are closest to the minority class instances. In the second step, the RENN algorithm repeatedly applies the ENN algorithm to the reduced majority class instances until no more instances can be removed. This process helps to further refine the majority class by removing any remaining noisy instances that were not detected in the first step. The result is a balanced dataset with an equal number of instances for each class. RENN sampling can be useful when the imbalanced dataset has a high degree of overlap between the minority and majority classes. However, like all sampling techniques, it has its limitations and should be evaluated carefully in the context of the specific problem and dataset being analyzed

➤ Output:

Total rows in balanced dataset: 1921  
Affected rows in balanced dataset: 533  
Unaffected rows in balanced dataset: 1388

#### RANDOM OVER SAMPLING

➤ Random oversampling is a simple technique for balancing the class distribution in an imbalanced dataset by increasing the number of examples in the minority class. This technique involves randomly duplicating examples from the minority class to increase their representation in the dataset. Random oversampling can be an effective technique for improving the performance of machine learning models on imbalanced datasets, especially for small datasets. However, this technique can also lead to overfitting and reduced generalization performance if not used appropriately. To avoid overfitting, it is important to use a validation set to evaluate the performance of the machine learning model during training and to select the best hyperparameters for the model

➤ Output:

Total rows in balanced dataset: 4368  
Affected rows in balanced dataset: 2184  
Unaffected rows in balanced dataset: 2184

#### SYNTHETIC MINORITY OVERSAMPLING TECHNIQUE

➤ SMOTE (Synthetic Minority Over-sampling Technique) is a popular data augmentation technique used to address class imbalance in machine learning. The SMOTE algorithm works by randomly selecting a minority class sample and finding its k nearest neighbours in the feature space. The synthetic sample is then created by randomly selecting one of these k neighbours and generating a new sample that is a linear combination of the selected neighbour and the original minority sample. By repeating this process for multiple minority class samples, SMOTE generates a set of synthetic samples that can be added to the original dataset to create a new, balanced dataset. The size of the synthetic dataset can be controlled by adjusting the ratio of 10 minority to majority class instances. SMOTE can be a useful technique for addressing class imbalance in a wide range of machine learning applications. However, it is important to note that SMOTE, like other oversampling techniques, can also introduce some noise or duplication into the data and potentially lead to overfitting. Therefore, it is important to carefully evaluate the effectiveness of SMOTE in the context of the specific problem and dataset being analyzed



➤ Output:

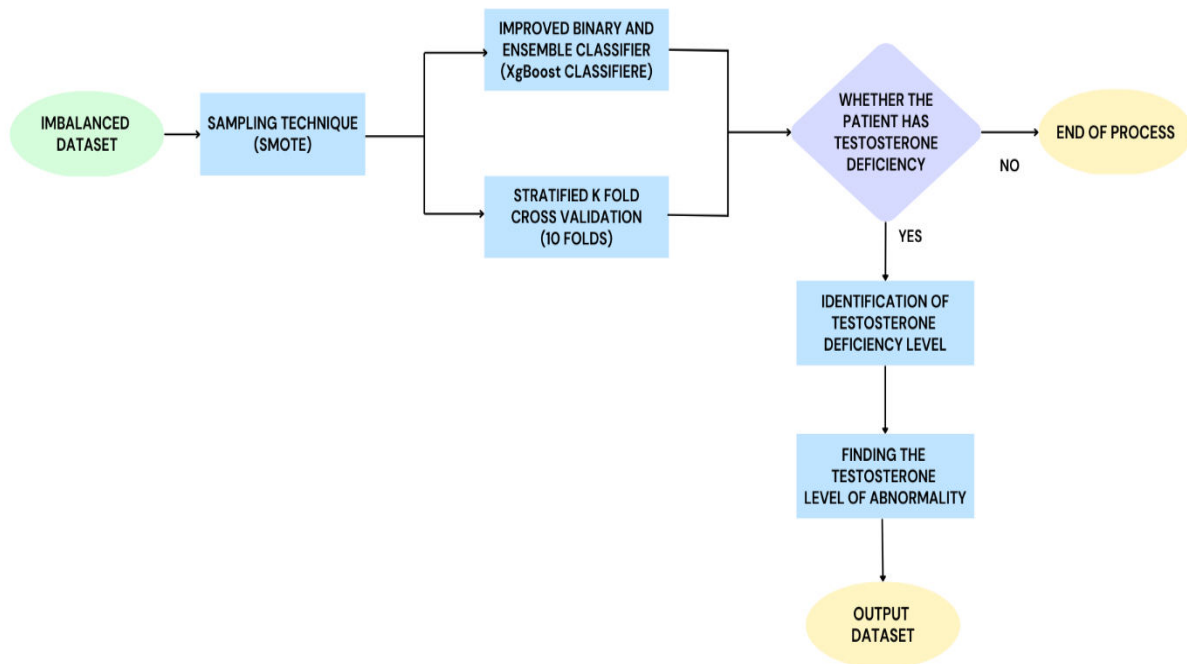
Total rows in balanced dataset: 4368  
 Affected rows in balanced dataset: 2184  
 Unaffected rows in balanced dataset: 2184

DATASETS	TOTAL ROWS	AFFECTED	UNAFFECTED
IMBALANCED DATASET	3397	655	2742
<b>UNDER SAMPLING</b>			
RUS	1066	533	533
RENN	1921	533	1388
<b>OVER SAMPLING</b>			
ROS	4368	2184	2184
SMOTE	4368	2184	2184
<b>HYBRID SAMPLING</b>			
RENN + SMOTE	2470	1235	1235
RUS + ROS	1312	656	656
RENN + RUS	812	156	656
RUS + SMOTE	1312	656	656

**Comparison of all Samplings**

**V. PROPOSED METHOD**

We propose a classification model for detecting testosterone deficiency using XG Boost, a popular gradient boosting framework. The proposed system addresses the issue of class imbalance in the dataset using SMOTE, a data resampling technique. The system then performs hyperparameter tuning using randomized search with stratified 10-fold cross-validation to find the best set of hyperparameters for the XG Boost model. The best model is then used to make predictions on the original dataset, and the accuracy scores are added as a new column to the original dataset. The system also creates a new column ‘abnormality\_level’ based on the accuracy score, categorizing the predicted results into low, medium, and high levels of abnormality provides a more nuanced and clinically relevant interpretation of the results, allowing healthcare providers to tailor treatment to individual patients’ needs. Overall, the proposed system achieves accuracy of 96%.



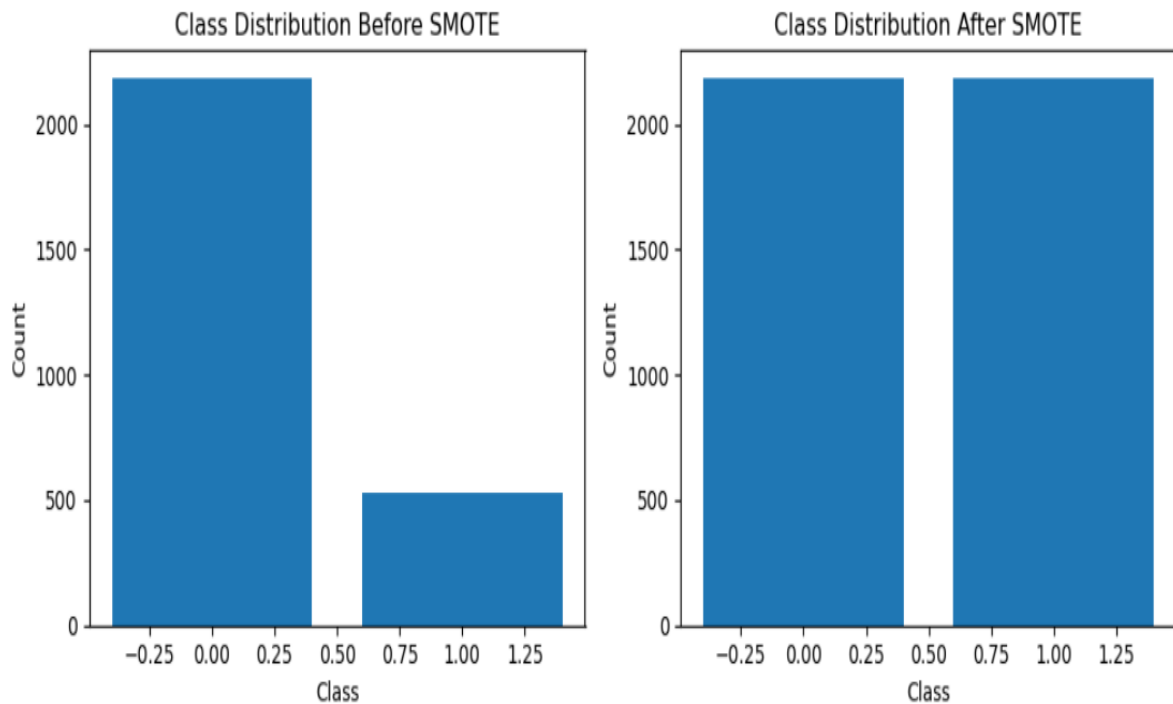
**Architecture Diagram**

In the proposed architecture, the methodologies SMOTE sampling is done for balancing the dataset; XGB classifier is improved using hyperparameter tuning with random search to train the dataset; stratified k fold cross validation; In the target column the data is either 0(No Testosterone Deficiency) or 1(Testosterone Deficiency). In the proposed model the testosterone deficiency is identified only for the rows with testosterone deficiency. So its filtered the dataset with only the rows has testosterone deficiency and identified the deficiency accuracy with abnormality levels like Low, Medium and High. This helps to patient to know about the deficiency level and generates into new dataset with new columns deficiency level and abnormality level.

**SMOTE**

Synthetic Minority Over-sampling Technique (SMOTE) is a popular oversampling technique for balancing the class distribution in an imbalanced dataset by generating synthetic examples for the minority class. The process of SMOTE involves selecting an example from the minority class, finding its k nearest neighbours in the feature space, and generating synthetic examples by interpolating between the feature vectors of the example and its neighbours. Specifically, SMOTE generates new examples by randomly selecting one of the k nearest neighbours of the selected example, computing the difference between the selected example and the neighbour, and adding a fraction of this difference to the selected example. This process is repeated until the desired level of balance between the minority and majority classes is achieved.

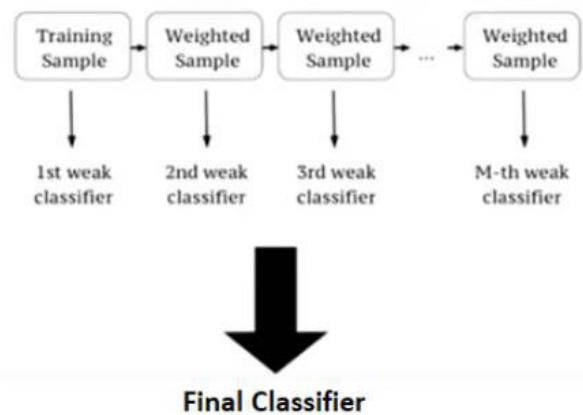




SMOTE Class Distribution

**XGBOOST**

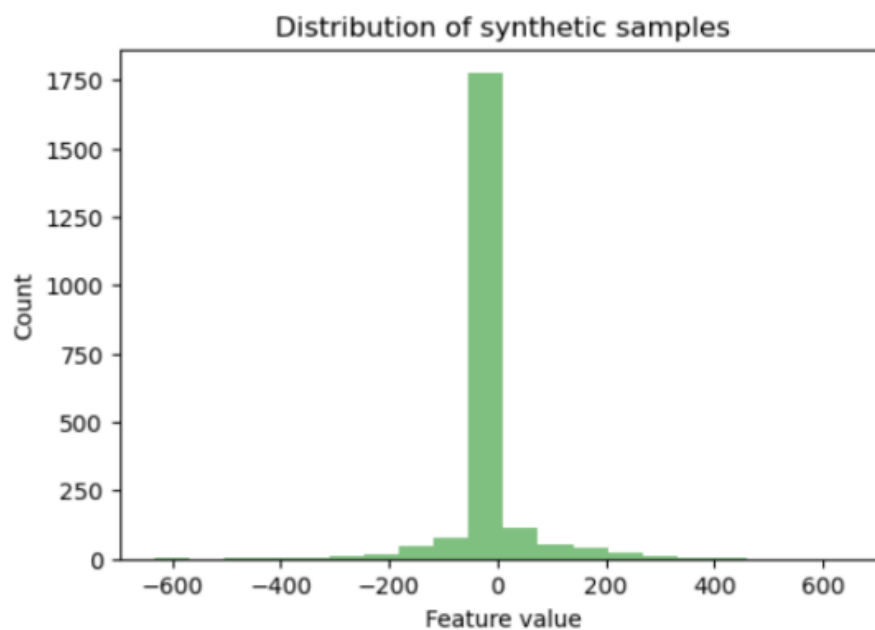
XG Boost is an implementation of Gradient Boosted decision trees. This library was written in C++. It is a type of Software library that was designed basically to improve speed and model performance. It has recently been dominating in applied machine learning. XG Boost models majorly dominate in many Kaggle Competitions. In this algorithm, decision trees are created in sequential form. Weights play an important role in XG Boost. Weights are assigned to all the independent variables which are then fed into the decision tree which predicts results. The weight of variables predicted wrong by the tree is increased and the variables are then fed to the second decision tree. These individual classifiers/predictors then ensemble to give a strong and more precise model. It can work on regression, classification, ranking, and userdefined prediction problems .



XGB Classifier

## VI. RESULT AND DISCUSSION

Testosterone Deficit Syndrome (TDS) significantly impairs men's quality of life, but its timely and accurate diagnosis poses a challenge in areas with poor access to public health services. TT and FT levels are not measured during routine inspections and their tests are often expensive. This leads to an effort to obtain cheaper predictive methods to filter and guide patients in undergoing further, more specific, and high-priced exams. Secondary hypogonadism occurs in conjunction with other disorders, which facilitates its detection. This paper presented a broad comparison of ten well-known ML classifiers, eight sampling methods for imbalanced datasets, and the calibration of the predicted probabilities to identify a proper method to improve accuracy in TDS diagnosis using only features obtained from low-cost routine exams. In the existing system, they try to improve the accurate level, which they got around 70 to 80% by using of the Classification algorithm, Sampling and Probability calibration. The use of different classifiers bearing low correlations between one another presents better results for the ensemble classifiers. In Sampling strategies, ML algorithms often present bad classification results in imbalanced data. This research compared eight sampling strategy combinations using the open-source python toolbox Imbalanced-Learn Random under sampling (RUS), Repeated Edited Nearest Neighbours (RENN), Random Over-Sampling (ROS), Synthetic Minority Over-sampling Technique (SMOTE), RENN + SMOTE, RUS + ROS, RENN + RUS, and RUS + SMOTE



### Synthetic sample in Dataset

#### DATASET NAME: FINAL\_OUTPUT\_DATASET

Using Xg Boost Model finding the deficiency percentage and abnormality level only for the patient which has testosterone deficiency. generates into new Dataset. Using Xg Boost with stratified k fold cross validation and hyperparameter tuning using random search helps to predicts the accuracy of 96.33% . the final accuracy of 96.33% and best combination of hyperparameter using XGB classifier along with cross validation and hyperparameter tuning using random search. Here, final output dataset with deficiency level for each rows and abnormality level.

Age	DM	TG	HT	HDL	AC	Level	Abnormality_Level
57	0	134	1	41	114	61.31	Medium
84	0	105	0	53	86	70.14	Medium
65	1	153	1	41	106	52.27	Medium
55	1	178	1	39	118	82.42	High
74	0	205	1	47	90	39.72	Low
70	1	180	1	64	108	75.69	High
62	1	142	1	33	118	78.7	High
71	1	134	1	35	108	88.18	High
57	1	137	1	37	121	68.06	Medium
47	0	120	0	41	102	55.9	Medium
60	0	83	0	44	107	80.51	High
61	1	434	0	40	103	91.79	High
56	1	121	0	50	108	67.61	Medium
67	1	87	1	43	108	38.61	Low
50	0	209	1	45	93	29.55	Low
69	0	165	1	66	112	91.12	High

#### Dataset using XG Boost

#### VII. CONCLUSION

Testosterone Deficient Syndrome (TDS) significantly impairs men's quality of life, but its timely and accurate diagnosis poses a challenge in areas with poor access to public health services. Eight sampling methods for imbalanced datasets, and the calibration of the predicted probabilities to identify a proper method to improve accuracy in TDS diagnosis. The use of these techniques significantly improves ML performance. In the existing system, they try to improve the accurate level, which they got around 70 to 85% by using the Classification and Sampling algorithm. In Sampling strategies, ML algorithms often present bad classification results in imbalanced data. In our proposed system. By using sampling techniques (Smote) we create a new dataset that is trained under Xg boost classifiers and stratified K fold cross-validation. The level of abnormality is presented by the age of the people lies between 0 to 40 is low, 41 to 70 is medium, 71 to 100 is High. Overall, we found the accuracy level up to 96% by using various algorithms. To improve the accuracy and effectiveness of a machine learning model, consider expanding the training dataset. To improve accuracy, the existing model might be refined with deep learning techniques like neural networks and other input qualities like lifestyle and medicine usage.

#### FUTURE ENHANCEMENT

Techniques to further improve the accuracy and effectiveness of the machine learning model for diagnosing Testosterone Deficient Syndrome (TDS) - Explore advanced sampling techniques beyond SMOTE (Synthetic Minority Over-sampling Technique) to address class imbalance more effectively. Techniques like ADASYN (Adaptive Synthetic Sampling) and Borderline-SMOTE can generate synthetic samples with more realistic characteristics, leading to improved model generalization and performance on imbalanced datasets.

And Develop hybrid models that integrate both traditional machine learning algorithms (e.g., XGBoost, Random Forest) and deep learning architectures (e.g., convolutional neural networks, recurrent neural networks) to leverage the strengths of each approach. Hybrid models can exploit complex nonlinear relationships in the data while maintaining interpretability and generalization ability.

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