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Pilot Study on Fibromyalgia Disorder Detection via XGBoosted Stacked-Learning with SMOTE-Tomek Data Balancing Approach

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Abstract

Emotional distress and functional disability amongst a plethora of other issues have marked themselves as symptoms of fibromyalgia, which is a chronic pain disorder that impacts about 12percent of global population. Characterized by widespread pain, fatigue and sleeping disturbances, fibromyalgia patients use opioids as immediate remedy to the unbearable pain experienced. While, this interplay between metabolomics, stress and pain are quite complex – experts have advised against the continued use of opioids. Thus, the quest for alternate treatment by healthcare experts seeks to use machine learning schemes in identification of fibromyalgia predictors, and monitor patient vitals. We study a stacked-learning scheme that fuse 3-models (Korhonen net, Genetic Algorithm and Random Forest) with XGBoost-regressor. With musculoskeletal dataset retrieved – we fuse Tomek-links with SMOTE for model prediction, which results in Accuracy 0.8002 with F1 0.8091 prior to the utilization of SMOTE; However, model yields perfect Accuracy and F1 with SMOTE-Tomek; And can successfully detect fibromyalgia disorder with enhanced performance/generalization.

1. Introduction

Population of persons living with fibromyalgia disorder – ranges from 1.2-to-5.4% of total global women's population [1]. As a disorder – fibromyalgia features widespread body pains. Symptoms include functional disability and emotional distress, which negatively impacts a carrier patient's quality of life [2]. There is today, a rise in trend with the number of persons living with the fibromyalgia disorder [3] – and the National Institute of Arthritis, Musculoskeletal and Skin disease has reported over $1-9billion spent on this disease in 2023 alone, with an expected growth 3.8% by 2034 and an accompanying monetization of over $2.9-billion dollars [4], [5]. Despite its high prevalence – there exists no single fit treatment as there is limited availability of pain-relieving therapy for many diseases [6] especially with fibromyalgia. Campaigns are today, aimed at the discontinuance of opioids to sporadically treat cum manage its associated pain – with healthcare experts advising against its prescription [7], [8]. But, its restrictive compliance is due to the fact that there is no available alternates; And this lack for a suitable alternate – continues to pose significant challenge for both healthcare professionals and patients therein [9], [10].

There is today the sporadic rise in death accompanied with underlying health conditions (a case in point of Nigeria) across the global landscape [11]. These anomalies have been attributed to the uncontrolled rise in pain and blood pressure causing hypertension and fibromyalgia, for which signs abound to include emotional stress and functional disability [12]. Rise in morbidity/mortality has crowned this disorder as a global health menace [13]. Opioids usage immediately help to relieve associated pain [14]; But, its asymptomatic nature, makes it a silent killer [15] and also as it conveniently masks underlying ailment in over 40years patients with a steady rise in cases of delayed diagnosis, and improper management [16]. With related deaths in USA reported as over 323,400-cases for 2023 [17] – and calls for the continued monitor of patients' vitals in efforts to battle fibromyalgia. The World Health Organization notes symptoms as hyperalgesia, opioids overdose/side-effects, immune-dysfunction, frequent/sudden hospitalization, and death [18], [19]. Its early detection via accurate vitals identification helps monitor patients and alert experts of patients symptoms [20]; And thus, mitigate the rise in mortality. As a non-communicable disease, makes it easier to diagnose – even when many patients self-manage [21]; while, many cases go unreported and untreated without a plan. Identification during clinical visits have been known to yield incomprehensive patient status [22]; Thus, proactive monitor via sensor observations is advised to gain (warning) early insights to aid quick interventions to help propose tailored treatment(s) for fibromyalgia patients [23].

1.1. Machine Learning Schemes: A Review

ML have proven useful in anomalies identification, which is achieved via their capability to learn intricate patterns inherent in task predictor(s) therein an (un)structured dataset [24]. Detection tasks are accomplished via classification or regression, utilizing vote, bagging, boost, and stacked modes [25]. Detection task can be divided into 3-groups: Machine Learning (ML), Deep Learning (DL), Ensemble Learning (EL). ML offers a wide-range of models, successfully trained to recognize evidence that supports a target class for high-dimension tasks [26]. Its flexibility and robustness allows ML to learn intrinsic patterns via feature engineering to decipher crucial predictor(s) selected for model construction and ease the detection of outliers [27], [28]. The drawback with ML includes: (a) model construction for enhanced accuracy and performance, (b) imbalanced dataset mode, and (c) flexibility of feature selection [29]. Common MLs are Random Forest [30], SVM [31], etc.

Deep Learning (DL) refers to neural networks (NN). They are best tailored to capture high-dimension patterns in time-series sequences [32], which are often dynamic, non-linear, chaotic and complex with examples in spatiotemporal cum medical dataset [33], [34]. Setback to the deep NN by default, is its poor generalization due to vanishing gradient problem which has often restricted its use. However, its variant – the Long-Short-Term Memory (LSTM) overcomes this via gates to control its input so that the model easily adapts to learn changes observed as long-term dependencies [35]. Its demerit is longer training time required and inability to handle large datasets [36]. Lastly, the ensemble learning mode effectively combines both ML and DL into a single classifier as its meta-learner to yield an optimal solution. It achieves this as follows via stacked, voting, bagging, and boosting schemes – to yield improved insight into the target domain [37], [38].

The stacked (transfer) learning mode trains a meta-learner (classifier) to efficiently fuse the predictive output of many base classifiers to make improvement on the meta (learner) classifier. This flexibility grants transfer learning mode the capability to yield enhanced outcome with lesser iterations [39]. With voting mode, classifier(s) are used independently to enhance performance of aggregated final output – without, fusion that relies on predictive relations. But, degraded performance can result from the diversity inherent the chosen dataset [40]. Also, bagging often trains similar tree-based classifiers such that each tree has equal voting weight(s). To uphold bias and variance, each classifier is trained via drawn (random) samples of training data. Model averages all the classifier predictions on the various classifiers to yield greater accuracy, on various subsets to reduce errors in bias-and-variance within a learner [41]. For boost mode, each iteration yields an improved ensemble that sequentially trains its base classifiers to corrects the mistakes inherent with its previous (base) learners. Resulting ensemble must learn with every iteration, the various intricate tasks its predecessors predicted incorrectly to yield enhanced generalization performance. A common boost is the Extreme Gradient Boost [42], [43].

1.2. Genetic Algorithm (GA) Model

GA as inspired by Darwinian evolution – is a stochastic optimization model that possess distinctive evolutionary features, programmed to learn intricate patterns in a dataset. It consists of a pool of potential solutions to a task [44]. Each candidate reaches optimum via four (4) operators (i.e. initialization, competence/fitness and selection, crossover, and mutation) [45]. The fit-function assess how close a solution is to the model's optimal solution so that only candidate solutions in close proximity [46] to the optimal solution's fit threshold are considered to be fit [47], [48]. Listing 1 below details the GA algorithm.

Algorithm Listing 1 for GA

Initialize /create an initial (zero) population with randomly generated candidates / individuals
declare initial_population, nos_elite_children, epoch, fraction_crossover_children, nos_mutation_chidren
function competence_computation()
  generate new pool: **selection type: rank**; tournament, steady-state, stochastic_universal_sampling, proportionate;
  offspring creation: new_individual(crossover and mutation): **exploit** replacement_strategies
end function
if true ← function competence_computation(generated_individuals)
  finishing criterion met then **proceed**
else finishing criterion not met → goto **label** start_of_a_cycle
end if: end GA_algorithm

1.3. Study Motivation and Gaps

The inherent gaps in previous studies includes [49], [50].

1. **Limited Dataset:** Medical dataset although scarce, are often large by nature and finding the right-formatted dataset as required for the machine learning scheme is challenging. Thus, the use of ML will yield an optimal fit solution that will properly encode and handle such categorical dataset [51], [52].
2. **Data Balancing**: An ensemble helps to investigate the impact of data balancing explored on its predictive power and analyze its effect on a model's capability to accurately predict cum yield the needed knowledge heralded by the enhanced performance [53], [54].
3. **Conflict Resolution**: In medical domain – the more complex the heuristic, the better the performance generalization. While, it is acceptable to utilize deep learning models, its complex nature makes them tedious to implement. Thus, we utilize ensemble technique that performs deep learning on non-expensive resources, to handle smaller-to-large dataset in lieu of sensitivity and specificity analysis as reached via area under curve (AUC) values. Also, two (2) conflicts arise with: (a) data encoding, and (b) structural dependencies for the hybrid learning [55]. We explore one-hot ending mode as means to resolve data encoding conflict as in Section 2.
4. **Comparative Analysis** evaluates the diverse schemes used within the constructed ensemble, to compare their relative performance and robustness in identifying the most suitable ones for predicting identification and classification of the fibromyalgia disorder [56], [57].

The, study contributes thus: (a) preprocessing to ensure data quality, (b) SMOTE-Tomek to improve distributions in class(es), (c) resolves structural dependencies conflicts with fusion of the 3-base models (i.e. Genetic Algorithm, Random Forest and Korhonen neural network), (d) utilize XGB meta-learner (using as input, the output of the fused base models) for fibromyalgia identification, and (d) test resulting stacked ensemble on fibromyalgia datasets to prove its efficacy and flexibility. Next, we discuss the proposed method, the results obtained from applying the method, and discuss the evidence found (in lieu of fibromyalgia identification) in a broader sense cum context. With systems built to improve electronic medical records management, the system must adequately assure users of data security to patient recordset [58], [59].

2.0. Materials and Methods

Our proposed method utilizes 3-base learners: (a) cultural genetic algorithm, (b) random forest, and (c) Korhonen modular neural net, and XGB meta-learner as in Figure 1 :

1. **Step-1 – Data Collection:** We retrieved the dataset via [web]:research.rug.nl/en/datasets/emo-fibro-dataset-of-woman-with-fibromyalgia". Dataset consists 584-fields, 203,498 transactions with 85,469 fibromyalgia (minor) cases and 118,029 non-fibromyalgia (major) cases [60], [61] as described in Table 1 as:
2. **Step-2 – Preprocessing**: Here, we perform the actions of cleaning as follows: (a) remove duplicate records to ensure dataset is devoid of redundancies, (b) remove missing values to ensure data quality, and (c) to yield an optimized, restructured dataset distributed into a variety of labeled-classes. We encode data via one-hot encoding mode so that model easily transforms categorical data onto their binary equivalent.
3. **Step 3 – Feature Selection** helps extract what labels will yield the input data (X), and determine what label will the ensemble predict as its output data (Y). In lieu of ground-truth, the fitness function seeks to remove all irrelevant/docile feats [62] that yield no significance or great importance in the quest for our target class. Like feature selection – it reduces dimensions of the chosen dataset and fasten model construction to yield improved performance [63] and devoid of poor generalization. It is suited for cases where cost is a critical factor [64], and its efficiency is evaluated by how well ensemble fits about ground truth [65]. With a threshold of 8.321 – a total of 7 features was used in lieu of the target class 1 [66] to aid insights into the contribution of different features to the classification process. We use Rosenbrock's function as in Equation 1 as the most common optimizer.

$$Y = 100 * \sum |(x_1^2 - x_2^2)^2 + (1 - x_1^2)^2| \quad (1)$$

4. **Step 4 – Data Balance/Split** tracks each predictor in lieu to domain target-class. Balancing redistributes the data-labels to ensure equally distributed (minor-and-major) class(es). We adapt a fused Tomek-links with synthetic over-sampling (SMOTE-Tomek) that achieve balancing thus [67]: (a) identifies minor-class, adjusts data-point(s) to those of its closest neighbors, (b) interpolates to create synthetic data-points from identified chosen neighbors, and (c) repopulates original pool with generated synthetic data to yield a balanced class distribution in domain dataset [68] as in Figures 2a and 2b respectively.

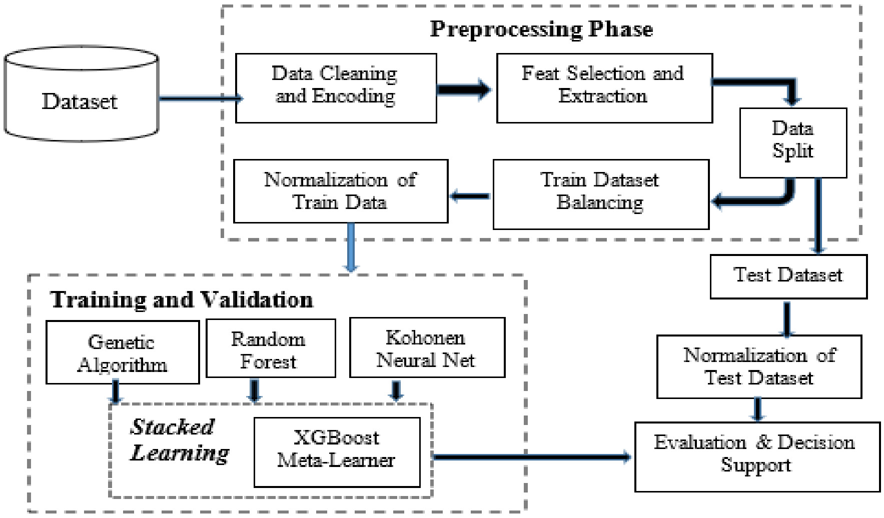

Figure 1. Proposed Stacking Ensemble Approach with XGB meta-learner

TABLE I. FITNESS RANKING OF FEATURES SELECTED FOR THE TOP-22 GENERATED RULES

Features	***Type***	***Format***	***Feature Description***
Gender	Object	abcd	Male, Female, Non-binary
Age	Object	abcd	Age of patient
marital_status	Object	abcd	Marital status of patient
occupational_pattern	Float	12:34	Current occupation
Monthly_income	Int	1234	Monthly income received
Years_diagnosed	Float	12.34	Years since fibromyalgia was diagnosed
Years_symptoms_appeared	Float	12.34	Years since symptoms appeared
Pharm_treatment	Float	M:D:Y	Pharmacological treatments received for fibromyalgia
substance_usage_disorder	Object	abcd	Use of substance/alcohol addiction during the period covered
Suicide_self-harm	Object	abcd	Number of attempts to commit suicide or involved in self-harm
Number_drugs_currently	Boolean	0/1	Number of drugs used currently daily
Number_drugs_crisis	Int	1234	Number of drugs used during crisis
Daily_dose	Object	1234	Daily dosage of opioids drugs utilized regularly and during crisis
Crisis_medication	Object	Abcd	Drugs utilized during crisis
Last_menstral	Int.	1234	Last menstrual cycle
Menstrual_cycle_duration	Int	1234	Duration of menstrual cycle
Menstrual_cycle_regu;arity	Boolean	0/1	Set as 1 if regular is True; Else set as 0 if False
Pain_intensity	Boolean	0/1	Set as 1 if pain is high; Set as 0 if Moderate, and Set as -1 if low
Total_widespread_index	Int	1234	Body parts for which the pain is experienced as shoulder, hips, back, jaw, hand, etc
Symptoms_experienced	Objects	abcd	Fatigue, muscle pain, blur vision, dizziness, vomit, easy bruising, headache, insomnia, depression, constipation, oral ulcers, seizures, heartburn, ringing in ears, light sensitive, hearing difficulty, numbness, rash, bladder spasms, painful urine etc
Resting_FMRI	Float	M:D:Y	Resting state FMRI performed
Patient_weight	Object	Abcd	Patient Weight
Patient_height	Float	12:34	Patient Height
Bmi	Boolean	0/1	Body mass index of patient
Imd	object	abcd	Daily dosage of morphine milligram equivalent
comorb_presence	object	Abcd	Charlson Co-morbidity index and presence
Fibromyalgia	Boolean	0/1	Target class for ground-truth: set as 1 if True and 0 if False

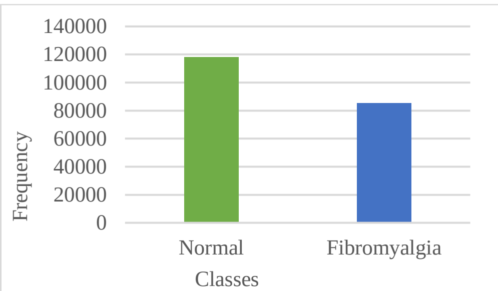

Figure 2a. Original Data plot

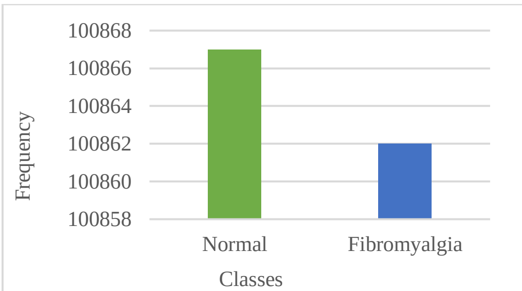

Figure 2b. Data balancing with SMOTE applied

5. **Step-5 – Normalization** use variable transformation to normalize the skewed dataset [69], [70]. This seeks to ensure a nearness in the class distribution and may result in a change in our data distribution. Features are

normalized via a standard scaler, which seeks to revert data features to yield a distribution which has a mean value of 0 and a standard deviation of 1. We achieve this via Equation 2 where x is the original value, μ is the mean, σ is the standard deviation, and z is the normalization process. Figure 3 shows normalized data plot for the minor-and-major classes distribution [71], [72].

$$z = \frac{(x - \mu)}{\sigma} \tag{2}$$

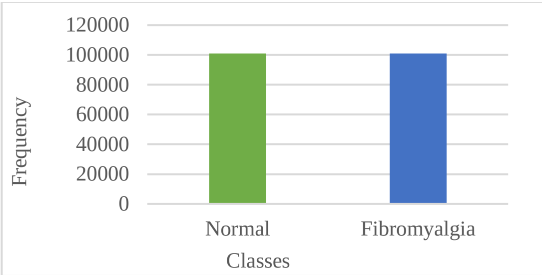

Figure 3. Normalized (with newly generated pool)

Then, dataset is split into 70% (70,607 records) as train-dataset, and 30% (30,260 records) as test-dataset.

6. **Step-5 – Stacked-Ensemble** fuses the outcome of 3-base learners to enhance the collective accuracy and generalization as it harnesses the prowess of its best-fit learners. These (CGA, RF and KMNN) are explained as:

a. GA: We adapt the variant Cultural GA, which utilizes belief spaces as: (a) normative belief establishes value ranges to which candidates are bound, (b) domain belief ensures that each candidate is equipped with requisite knowledge, (c) temporal belief ensures that each of the candidate solution is knowledgeable at the task solution, and (d) spatial belief equips each candidate with task's topological knowledge. Our CGA utilizes an influence function to set both bounds (upper/lower) and to transfer available knowledge between its population pool and the belief space(s); And in turn, alters to ensure candidates in the pool conforms with the belief space. CGA ensures the pool that does not violate its belief space – to help reduce number of candidates generated till an optimum is found [73]. Table 2 details the configuration for CGA.

TABLE II. CGA PARAMETER DESIGN AND CONFIGURATION

Features	***Value***	***Description***
max_nos_gen	120	Maximum number of generations
nos_individuals	30	Number of solutions in a generation
selection_type	int	1-rank, 2-elitism, 3-steady_state, 4-toruney, 5-stochasticUniversalSampling
offspring_creation	int	Probabilities of offspring generation for: 1-crossover, 2-mutation
req_fit_function	10	Minimal number of samples needed
learning_rate	0.1	Determines step-size in learning
random_state	25	The seeds for reproduction
max_nos_gen	10	Max iterations with no solution improvement
max_nos_gens	120	Maximum number of generations (i.e. epoch)

b. **Random Forest** ensemble utilizes the bagging model to grow successive trees independently. It uses bootstrap aggregation to construct each tree and to sample its train data using a majority vote at its prediction [74]. RF extends randomness via an extra layer that changes how it constructs its trees. Each node is split using binary-tree predictor, as RF split its nodes and randomly selects best predictor node from its learner(s)t. Its recursive structure helps it to capture interactions [75] between various predictors. Its drawback is in their flexibility [76] with data diversity and complexity [77] as its outcome can yield lesser performance for ground truth. To curb this, we adopt hyper-parameter tuning to greatly reduce model overfit, address imbalanced datasets, and enhance accuracy in its quest for ground truth [78], [79]. Table 3 shows the RF configuration.

TABLE III. RANDOM FOREST PARAMETER DESIGN AND CONFIGURATION

Features	***Value***	***Description***
n_estimators	150	Number of trees constructed
learning_rate	0.25	Step size learning for update
max_depth	5	Max depth of each tree
max_features	5	Max features to construct the RF tree
min_sample_leaf	auto	Number of feats to be considered
min_sample_split	10	Minimal samples needed
min_wt_fract_leaf	0.1	Tree's weight assigned to each sample
random_state	25	The seeds for reproduction
eval_metric	error, logloss	Performance evaluation metrics
eval_set	x,val, y_val	Train data for evaluation

verbose	True	Checks if evaluation metric is printed
bootstrap	True	Ensures bootstrap aggregation use
warm_start	False	Ensure the tree does not restart

c. **Korhonen Modular Neural Network (KMNN)** as [80] yields a deep neural net with modular learning ability, which receives input from CGA – and computes output via tan-sigmoid transfer function. It splits a network into smaller units for improved efficacy that exponentially increases independence of added units. Its modular mode improves its computational efficiency with reduced time convergence on task (as it split and handles task via modular units) [81]. Thus, tasks are executed in parallel and re-assembled on completion to improve model's flexibility. It exploits CGA's belief spaces to ensure no candidates leap outside its established bounds – as diversity is granted via independent training algorithms used by each unit. Modularity makes for a more robust and flexible network with improved generalization [82]. This also allowed for eased learning of intricate feats of interest as contained therein the dataset. Finally, data is transferred via task decomposition and training in lieu of ground-truth. Our KMNN is constructed from a set of multi-layer perceptron network with backpropagation in time (unsupervised) learning approach [83]. Table 4 details the KMNN configuration.

TABLE IV. KORHONEN NEURAL NET DESIGN AND CONFIGURATION

Features	***Value***	***Description***
eval_perf_set	MSE	Performance evaluation metrics at training
neural_net_used	Korhonen	Type of neural network adapted
hidden_layers	10	Amount of hidden layers adopted
input_nodes	2	Amount of input nodes
output_node	1	Amount of output node required
output_neurons	1	Amount of the output layer neuron(s)
hid_layer_neurons	1	Amount of the hidden layer neurons
validation_percent	25	k-fold partition dataset used for testing
training_percent	50	k-fold partition dataset used for training
retraining_percent	25	k-fold partition dataset used for retraining
transfer_hidden	tan-sigmoid	Transfer (activation) learning function used at hidden layers
learning_rate	0.25	Step size learning to update ensemble
transfer_ouput	pure line	Transfer learning function at output layer
max_nos_train	500	Max iteration of each network
number_layer	10	Minimal number of samples needed
data_division	random	k-fold dataset partition for construction
validation_check	6	Tree's weight assigned to each sample
train_net_algo	LMBP	Training mode adopted by neural network
bkpg_momentum	auto	Backpropagation with momentum learning
weight_one_two	auto	Nodal weight for variance

d. **XGB** tree-based leaner, scales gradient boost to classify data. It yields a stronger learner, aggregating its weaker (base) learner tree via majority voting schemes over a series of iterations on data points to yield an optimal fit solution. It expands its goal function by minimizing its loss function to yield an improved model to manage tree complexity more effectively. For optimality – the XGB leverages the predictive power of weak base learners, to yield a better decision tree with each iteration and account for the weak performance that contributes to its knowledge about the task. Thus, with each tree trained on the candidate data, it expands the objective function via regularization term $\Omega(f_t)$ and loss function $l(Y_i^t, \hat{Y}_i^t)$ as in Equation 3 to yield an appropriate fit ensemble with improved generalization. This, ensures that both training dataset fits as re-calibrated solution to remain within its solution's set boundaries, and tunes its loss function for higher accuracy [84] configuration design as in Table 6.

TABLE V. XGBOOST PARAMETER DESIGN AND CONFIGURATION

Features	***Value***	***Description***
n_estimators	250	Number of trees constructed
learning_rate	0.25	Step size learning to update the ensemble
max_depth	5	Max depth of each tree
random_state	25	The seeds for reproduction
eval_metric	'error', 'logloss'	Performance evaluation metrics
eval_set	x,val, y_val	Train dataset to evaluate performance
verbose	True	Checks if evaluation metric is prints

7. **Training**: Our ensemble learns from scratch using train (normalized) dataset. The ensemble identifies intrinsic patterns present in each k-fold (in-sample) partitioned dataset as guaranteed by the base-learner comprehensive learning. With hyperparameters set for the base learners and weights adjusted in lieu of gradient loss [85] – to recognize how fast the ensemble learning abandons old beliefs for newer ideologies during training. Our meta-learner yields a higher learning rate because the ensemble changes quickly as it learns newer feats. This flexibility

yields ease of adaptability. The XGB meta- learner utilizes the regularization terms to change during learning quickly and ensures it adequately adjusts its learning to be devoid of poor generalization. We tune the predictors: learn_rate, max_depth, n_estimator and booster to ensure optimal performance [86], [87].

4.0. Results and Discussion

Table 6 shows ablation report of 3-base learners (CGA, RF and KMNN respectively) with XGB-regressor as meta-classifier. The structural conflict was resolved by fusing first, CGA and KMNN as in Section 2 – and leveraging the tree-based RF to resolve computational complexities and diversity in the dataset used. This ensures ensemble is devoid of overfit with its base-learners as in Table 6, which shows the result of the ensemble prior the application of SMOTE-Tomek links with XGB-regressor aimed at boosting the stacked learning approach as explored. This, agrees with [88], [89]. Prior the utilization of SMOTE-Tomek, our base-leaners (i.e., CGA, RF, and KMNN) yields Accuracy 0.7029, 0.7340 and 0.7902 - with F1 0.7105, 0.7356 and 0.7868 respectively. Their respective Precision and Recall are as in Table 6. Also, the XGB meta-learner yields Accuracy 0.8002 and F1 0.8091 with Precision and Recall as represented therein in Table 6. With 'before' and 'after' scenarios – both KMNN and RF outperforms CGA, which agrees with [90]; while the XGB-regressor leans on the ensemble's robustness and flexibility to yield improved generalization, which agrees with [91].

TABLE VI. PERFORMANCE EVALUATION FOR 'BEFORE' SMOTE APPLIED

Models	*F1*	Accuracy	Precision	Recall
Cultural GA	0.7105	0.7029	0.6945	0.6985
Random Forest	0.7356	0.7340	0.7045	0.7102
Korhonen MNN	0.7868	0.7902	0.7920	0.7922
Meta-Learner				
XGB	0.8091	0.8002	0.7992	0.7992

TABLE VII. PERFORMANCE EVALUATION FOR 'AFTER' SMOTE APPLIED

Models	*F1*	Accuracy	Precision	Recall
Cultural GA	0.9727	0.9715	0.9724	0.9805
Random Forest	0.9768	0.9783	0.9784	0.9876
Korhonen MNN	0.9781	0.9824	0.9810	0.9895
XGB	1.0000	1.0000	0.9999	1.0000

Furthermore, as in Table 7, the usage of SMOTE-Tomek ensured the base-learners (CGA, RF, and KMNN) yielded an improved Accuracy of 0.9715, 0.783 and 0.9824 – with F1 of 0.9727, 0.9768 and 0.9781 respectively [92]. Their respective Precision and Recall are as in Table 7; while, the XGB meta-learner yields perfect Accuracy, Recall and F1 with Precision of 0.9999, which agrees with [93]. Figure 4 shows the confusion matrix for the ensemble.

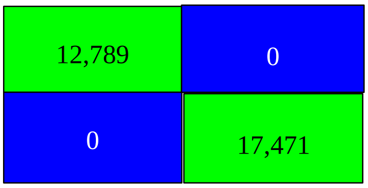

Figure 4. Ensemble Confusion Matrix

The use of SMOTE-Tomek and Competence fitness yield several benefits: (a) yields fewer predictors with greater significance in lieu of ground truth, (b) ensure faster model construction and training due to dimensionality reduction with chosen dataset [94], [95], (c) assures reduced training time, especially for such scenario where early detection is crucial to usher quick treatment plan and response [96], [97].

Table 8 yields the time convergence for 'before' and 'after' scenario for the ensemble approach.

TABLE VIII. CONVERGENCE TIME FOR 'BEFORE' AND 'AFTER' CASES

Models	Before		After	
	Time	Epochs	Time	Epochs
CGA	332sec	108-iterations	128secs	93-iterations
RF	123secs	215-iterations	95secs	69-iterations
KMNN	208sec	90-iterations	89secs	73-iterations
XGB	118sec	78-iterations	89secs	43-iterations

We observed it took an average 118sec in 78-iterations for the XGB-regressor to yield its best fit solution without the application of SMOTE-Tomek; while, CGA, RF and KMNN reached optimal fit (prior applying SMOTE-Tomek) at 332secs with 108-iterations, 123secs in 215-iterations, and 208secs with 90-iterations respectively. Conversely, applying SMOTE-Tomek – XGB yields best fit at 89secs with 43-iterations; while, CGA, RF and KMNN yields best fit at 128secs with 93-iterations, 95secs with 69-iterations and 89secs with 73-iterations respectively.

4.1. Comparison / Benchmarking

In seeking to compare ML-solutions for fibromyalgia that have utilized the same dataset as presented herewith – we found a few. And while, some domain task have proven easier to be identified; Medical domain can be quite painstaking [98] as the chosen ensemble design and metric are strongly correlated as a consequence of diagnostic errors in the captured dataset. Thus, both specificity and sensitivity factors are critical cum crucial underlying feature of interest that evaluates directly to the patient clinical outcomes. Whilst some tasks have proven much easier to classify [99]; Others, have are more painstaking such as task(s) with image and medical data, which requires the chosen model to explore metrics such as specificity – with strong impacts on the consequence of a diagnostic error [100]. Thus, specificity is a critical feat that must be evaluated as it directly relates to a patient's clinical output. Furthermore, with stacked ensemble – we must resolve conflicts from: (a) data encoding from one model to another, and (b) structural dependencies imposed by adopted model. We resolved data-encoding conflict via one-hot encoding technique which successfully converts all categorical data into their binary equivalence and proper format for use by the proposed ML.

TABLE IX. BENCHMARK / COMPARATIVE TESTING OF METHOD

Methods	*Accuracy*	*Precision*	Recall	F1	Spec.
Ref [17]	1.0000	1.0000	0.9999	1.0000	1.0000
Ref [101]	0.9981	0.9800	0.9800	0.9800	0.9995
Ref [102]	0,9968	0.9318	0.9848	0.9881	-
Ref [103]	0.9999	0.9997	0.9991	0.9997	-
Ref [104]	1.0000	1.0000	0.9999	1.0000	1.0000
Our Method	1.0000	1.0000	1.0000	0.9999	1.0000

5.0. Conclusion

This study implements a robust ML-solutions targeted at fibromyalgia identification/classification that fuses the power CGA, RF, and KMNN (learners) with XGB meta-learner. It utilized the SMOTE-Tomek balancing with the competence fitness computation to yield fewer predictors that are of greater significance to ensure a faster model construction and training due to dimensionality reduction. The SMOTE-Tomek and the base learners can increase accuracy, precision, recall and model specificity. Despite the large and complex health data [105], the stacked ensemble successfully utilized SMOTE-Tomek – XGB to yield enhanced performance and generalization. This finding indicates that ensemble techniques with a rigorous meta-learner can minimize the individual weaknesses of each ML model and thus emphases the importance of a hybrid approach in classifying, predicting inconsistent data variance in medical datasets. So, for the future of early disease identification and classification, this pilot study is a positive step and should be improved upon.

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