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Investigating Fibromyalgia Detection via SMOTEENN-fused XGBoosted Stacked Learner

AKO, E. A.[1,*], *AGBONKPOLO, P.*[1], *ONOMA, P. A.*[3], *OMOSOR, J.*[1], *ANTHONY-AKHUTIE, P.*[1], *MAX-EGBA, A. T.*[1], *NIEMOGHA, S.*[1]

[1]*Department of Computer Science, College of Computing, Federal University of Petroleum Resources Effurun, Delta State*

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ABSTRACT

The Fibromyalgia syndrome is a chronic pain disorder that affects between 2-4% of global population with diagnostic challenge that relies on subjective symptom assessment, and absence of specific biomarkers. This leads to delayed diagnosis and suboptimal result for patients. However, learning schemes have been explored to aid quick detection of fibromyalgia with limitations including small data set, single-model dependence, and mishandle of complex clinical data relations. These have necessitated the deployment of a more robust analytical frameworks, which this study seeks to advance that will address the gaps. We propose an ensemble that fuses three (3) base learners with XGBoost. With dataset imbalance resolved via SMOTEENN, results show superior performance with our ensemble achieving 1.000 for Accuracy, F1 and Precision with 0.999 for Recall and 18secs runtime efficiency. Report affirms our ensemble's enhanced generalization, and validates its fusion with proper feature selection and data balancing can substantially improve fibromyalgia detection to provide clinicians with a robust tool for early diagnosis to facilitate timely intervention strategies and improved patient care outcomes in clinical settings.

1. INTRODUCTION

There is today, a rise in death rate as experienced by many patients' underlying health conditions (Ejeh et al. , 2024). With the fibromyalgia disease poorly misunderstood overtime, its prevalence in pre-menopausal and menopausal women phases (Allan-Blitz et al. , 2024) has witnessed a sporadic upsurge that has today – morphed the diagnostic criteria therein which has evolved in parallel with an improved understanding of clinical manifestations (Karacaoglu et al. , 2024). With initial scepticism, fibromyalgia has become a global health menace impacting over 4percent of global women population (Ojugo *et al.* , 2024) and yielding a prevalence that transcends demographic boundaries. At its core, fibromyalgia is best described (as in women at pre-/menopausal stages) is a chronic, medical condition (Barua et al. , 2023) with widespread musculoskeletal pain and fatigue that is often associated with sleep aponia cum disturbance (Assumpção et al. , 2009). Also known as fibro-fog (Houck *et al.* , 2019), is a non-immune, non-inflammatory dissociative pain disorder (Odiakaose et al. , 2025) that alters pain processing in a body's nervous system, and has been attributed with cognitive difficulties, depression (Setiadi, Ojugo, et al. , 2025), irritable bowel, mood problems (De Girolamo et al. , 2012), etc. While, many had

*Corresponding author, e-mail: patience.akhutie@gmail.com, kenbridge14@gmail.com, joy.omosor@gmail.com, ako.rita@fupre.edu.ng, abere.reuben@fupre.edu.ng, geteloma.victor@fupre.edu.ng

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mistaken it as a rheumatic disorder, fibromyalgia is a pain disorder (Behera et al. , 2022) with heightened sensitivity to the tactile stimuli (Eboka, Odiakaose, et al. , 2025) in the nervous system. The quest for the quick relief to such excruciating pain associated with this disease (Zuama et al. , 2025) – led to the development and deployment of treatment plans that involved the prescription of opioids (Hedegaard et al. , 2021), which in turn – has become extremely useful in the immediate relieve of the associated pain (Pratama et al. , 2025; Scherrer et al. , 2017).

While opioids remain quite relevant today, the World Health Organization (WHO) has acknowledged the symptoms associated with its prescription (Alobalorun Bamidele et al. , 2020; Zetterman et al. , 2024) to include immune dysfunction (Lötsch et al. , 2022), hyperalgesia, overdose, and in extreme cases – death. Thus, the urgent call by experts and clinician to aid the early detection of the fibromyalgia disorder via the effective measure of patient vitals as accurate predictors for its proper identification (Onoma, Agboi, Geteloma, et al. , 2025), its diagnosis and commencement of early treatment plans will effectively help to monitor patients vis-à-vis alert clinicians of the accompanying symptoms in observed patients – that leads to mitigating the rise in fibromyalgia-associated mortality (Janet Kuramoto et al. , 2012). Its spectrum as a non-communicable (Jornada et al. , 2024) eased its diagnosis so that some patients self-manage, as other cases go unreported and untreated (Ghasemieh et al. , 2023). Even with clinical visits, identifying the disease yields incomprehensive patients' status (Hedman-Lagerlöf et al. , 2024); And czars advice the continued monitor of patients to avoid a ripple of its symptoms across a patients' underlying ailments (López-Muñoz et al. , 2023). Healthcare infrastructures monitors via sensor-based observations that acquire early-warning data so that clinicians can offer quick, apt and patient-tailored interventions (Muslikh et al. , 2023; Setiadi, Muslikh, et al. , 2024; Setiadi, Sutojo, et al. , 2025). Even so, experts continue to seek alternates to early prognosis of the disease, via growth advances in the field of informatics (Aghaunor et al. , 2025; Ifioko et al. , 2024).

Learning models have since become veritable tools with carefully refined parameters that helps us construct/train a system to effectively identify a task (Okofu, Anazia, et al. , 2024). Adequately trained schemes are used to detect anomalous patterns in healthcare – even with the always changing dynamics with prevailing patient vitals as predictors (Malasowe, Ojie, et al. , 2024). Learning schemes are grouped into machine learning (ML) (Agboi et al. , 2025), deep learning (DL) (Yoro et al. , 2025), and ensemble learning (EL) (Odiakaose et al. , 2024). The flexibility, robustness and reusability of MLs lend itself to learn intrinsic data patterns and decode selected predictors that fastens model construction (Islam et al. , 2021; Malasowe, Edim, et al. , 2024), and eases the identification of outlier data (Setiadi, Muslikh, et al. , 2024) for a specific task. Its pitfall(s) is often witnessed around dataset imbalance vis-à-vis the mode of feature selection adopted (Srivatsan et al. , 2022; Ugbotu et al. , 2025). With MLs fast-paced replaced by DLs (Malasowe, Okpako, et al. , 2024) – DL schemes are based on recurrent neural networks (RNN) – and can capture high-dimensional, dynamic patterns as in fibromyalgia datasets (Malasowe, Aghware, et al. , 2024; Ojugo & Eboka, 2021). However, its yields poor generalization due to its vanishing gradient problem that restricts its usage. To overcome this, we use gates to controls its input, easing its adaptability to the changes learned. The demerit is that this feat requires longer training time, and the heuristics' inability to handle large datasets (Dong et al. , 2024). To resolve the conflicts imposed on DL by either its variants or their nature – we explore the EL scheme, which effectively hybrids the ML-and-DL into a stronger learner (Muhamada et al. , 2024) via either voting,

transfer, bagging, and boosting (learning) modes to enhance its generalization into the target domain. This fusion must be able to resolve structural and encoding conflicts while leveraging the merits of both ML and DL to avoid model overfit as birthed by the underlying models (Ben Yahia et al. , 2022; Otorokpo et al. , 2024). In addition, resolving dataset imbalance as a crucial task, and many studies have explored and continues to use oversampling schemes (Okpor, Aghware, Akazue, Eboka, et al. , 2024; Okpor, Aghware, Akazue, Ojugo, et al. , 2024) as opposed to the under-sampling approach that is poised to reduce, and in many cases – make meaningless the task dataset (Sinayobye et al. , 2023). A common oversampling scheme is the synthetic minority oversample technique (SMOTE), and its variants SMOTE-Tomek (Akazue, Okofu, et al. , 2024) and SMOTEENN (Muslikh et al. , 2023; Setiadi, Susanto, et al. , 2024).

Our XGB leans on its base learners, to reduce overall bias and enhance its generalization (Binitie et al. , 2024). Our study: (a) identifies patient vitals as fibromyalgia symptoms (Safriandono et al. , 2024), (b) resolves dataset imbalance via SMOTEENN (Brizimor et al. , 2024), and (c) selects identified predictors via relief ranking feature selection (Urbanowicz et al. , 2018). Our study contributes thus (Ojugo & Yoro, 2021; Setiadi, Sutojo, et al. , 2025): Section 1 introduces the subject with gaps, (b) Section 2 explores the proposed method – leaning on data collection, pre-processing, data split-balance-normalize, train XGBoosted stacked model (Onoma, Ugbotu, et al. , 2025), and (c) Section 3 – discusses the obtained results as evidence in a broader context of fibromyalgia (Ako et al. , 2024; Ojugo, Ejeh, et al. , 2023).

2. *MATERIALS AND METHODS*

Our proposed methodology is as thus:

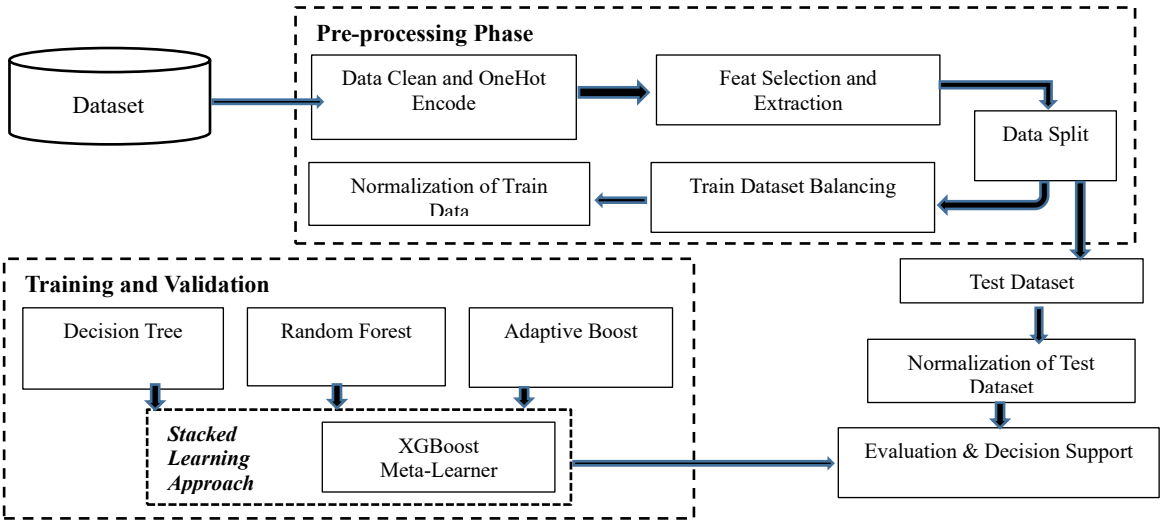

Figure 1. Proposed System Architecture

Step-1: Data Collection was retrieved via [web]:research.rug.nl/en/datasets/emo-fibro-dataset-of-woman-with-fibromyalgia" (Ako et al. , 2025) – consisting of 203,498 records with 85,469 fibromyalgia cases, and 118,029 non-fibromyalgia cases as in Figure 2, which shows the plot of the original classes distribution; whereas Table 1 yields the dataset structure.

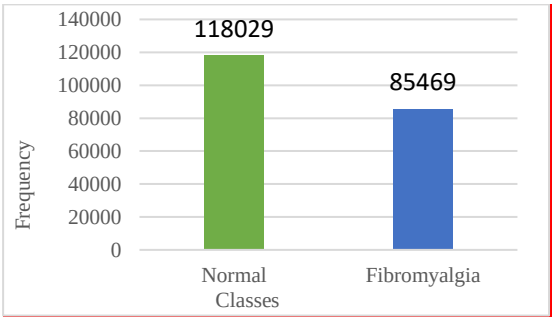

Figure 2. Original dataset plot

Step-2 – Pre-processing cleans up the

dataset by expunging redundancies to yield data integrity, and removes missing values to yield data quality (Jiang et al. , 2024; Omodunbi et al. , 2024). This optimized dataset is then encoded via a one-hot encoding, which transforms the categorical into equivalent binary forms. Figure 6 shows the optimized dataset.

Step 3 – Relief Rank Feature Selection reduces dataset dimensionality by expunging docile features, selecting only relevant predictors that will fasten model construction (Said et al. , 2023). We use the relief ranking mode as thus: (a) assume all features are same weight, (b) identify nearest sample as a hit, and farthest sample as a miss, and (c) uses feature value of nearest samples to update weight(s) (Okpor et al. , 2025), with predictors' correlation for a target class (Ojugo & Nwankwo, 2021a, 2021b). With our value of computed threshold of 8.321 – it ranks all predictors as in Table 1 with a total of 25-features selected from the initial 27-features as in the original dataset.

Step 4 – Data Split/Balance: Dataset is first, split into train (75%) and test (25%). We then balance the dataset by interpolating its nearest neighbour to create synthetic points that help repopulates-or-removes from the original pool to yield a balanced dataset as in Figure 3. We adapt **SMOTE-EEN** – a hybrid SMOTE (oversampler) and ENN (under-sampler) detailed as in (Aghware et al. , 2025). Figure 3 shows balanced plot with approach in Algorithm 2.

Table 1. Dataset Description

Features	Format	Feature Description	Select
gender	abcd	Male, Female, Non-binary	Yes
age	abcd	Age of patient	Yes
marital_status	abcd	Marital status of patient	No
occupational_pattern	12:34	Current occupation	Yes
Monthly_income	1234	Monthly income received	No
years_diagnosed	12.34	Years since fibromyalgia was diagnosed	Yes
years_symptoms	12.34	Years since symptoms appeared	Yes
Pharm_treatment	M:D:Y	Pharmacological treatments received for fibromyalgia	Yes
substance_use_disorder	abcd	Use of substance/alcohol addiction during the period	Yes
Suicide_self-harm	abcd	Suicide attempts, or involved in self-harm	Yes
Number_drugs_currently	0/1	Number of drugs used currently daily	Yes
Number_drugs_crisis	1234	Number of drugs used during crisis	Yes
Daily_dose	1234	Daily opioids dosage utilized regularly and during crisis	Yes
Crisis_medication	Abcd	Drugs utilized during crisis	Yes
Last_menstral	1234	Last menstrual cycle	Yes
Menstrual_cycle_duration	1234	Duration of menstrual cycle	Yes
Menstrual_cycle_regu;arity	0/1	1 if regular is True; Else set as 0 if False	Yes
Pain_intensity	0/1	1 if pain is high; 0 if Moderate, and Set as -1 if low	Yes
Total_widespread_index	1234	Body parts for which the pain is experienced	Yes
Symptoms_experienced	abcd	Fatigue, pain, insomnia, ulcer, depression, heartburn, etc	Yes
Resting_FMRI	M:D:Y	Resting state FMRI performed	Yes
Patient_weight	Abcd	Patient Weight	Yes
Patient_height	12:34	Patient Height	Yes
bmi	0/1	Body mass index of patient	Yes
imd	abcd	Daily dosage of morphine milligram equivalent	Yes
comorbity_presence	Abcd	Charlson Co-morbidity index and presence	Yes
fibromyalgia	0/1	Target class for ground-truth: set as 1 if True and 0 if False	Yes

Algorithm 2: SMOTE-ENN Data balancing approach

1. from sklearn.select import train_test_split, StratifiedShuffleSplit //stratified data split with train-75% and test-25%
2. xy_train, = train_test_split (testSize=0.25, trainSize=0.75, stratify=y, random_state=42)
3. x_val, x_test, y_val, y_test = train_test_split(x_temp, y_temp, test_size=0.25, stratify=y_temp, random_state=42)
4. from minor_class, choose random data-point *//start SMOTE_mode*
5. compute: rel_dist from rnd_selectData and k_nearest_neighbor
6. choose rnd_val = random_value(0,1): rnd_val * rel_distance;
7. **if** simSamples = obtained **then** minorClassNew = minorClas + simSample

8. repeat steps 2-to-4 until threshold_minor_class_new = reached;
9. select rnd_minor_class(data) //start ENN (under-sampler) approach
10. find k_nearest_neighbor(randomized_data): **if** knn.selected = minor_class_new **then** EEN_link created
11. stop ENN procedure: end

Step-5 – Normalization transforms a skewed (varied) dataset (Ojugo et al. , 2013) to ensure a nearness in the class distribution. We use the z-score normalizer as it can handle outliers to yield a distribution mean of 0, and deviation of 1 as in Equation 1 – where x is value, μ is mean, σ is standard deviation, and z is the normalizer process. Figure 3 shows normalized data plot (Ojugo et al. , 2015; Oyemade & Ojugo, 2020).

$$z = \frac{(x - \mu)}{\sigma} \quad (1)$$

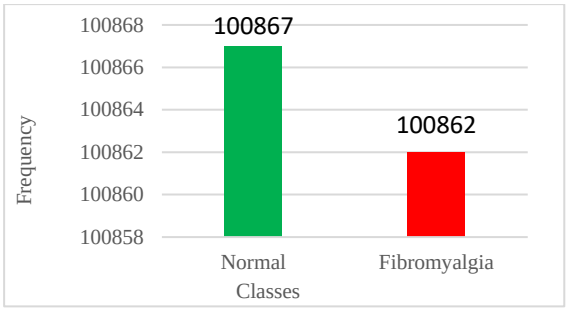

Figure 3. SMOTEEN balance data plot

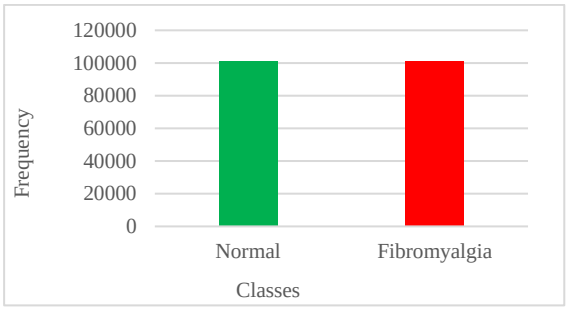

Figure 4. Normalized data plot

Step-6 – Stacked-Ensemble fuses 3 base learners to enhance the collective accuracy that harnesses the prowess of its best-fit learners explained as thus :

1. **Decision Tree** as a single, tree-learner utilizes intricate sampling, starting from its root to compare values with records attribute – and branch off thus: (a) begins at a tree root S that consists of complete dataset, (b) finds the best attribute via attribute selection, (c) divide S into train/test subsets containing values for the best attributes, (d) generate decision tree node with best attributes, and (e) recursively make new decision trees via subset created (Umarani et al. , 2021). It continues until an optimal criterion is reached and tree can no longer classify the nodes via pruning (error or cost) of a leaf node. Its demerits are: (i) complex due to its many layers, (ii) result in overfit, and (c) increased computational complexity for large datasets. Table 2 shows the Decision Tree design configuration.

Table 2. Decision Tree Configuration

Features	Value
infoGain	120
learnRate	0.25
minSampleSplit	10
evalSet	(x,val, y_val)
minWeightFractionLeaf	0.1
maxDepth	5
randomState	25

2. **Random Forest** grows its decision trees independently via the bootstrap-based, bagging approach (Emordi et al. , 2024). It uses a binary split on its extra layer to extend the randomness of how its trees are grown with its best nodes randomly selected to capture intrinsic underlying feats in the dataset. Its inability to handle chaotic diversity (Aghware et al. , 2024) in categorical data results in poor generalization – allowing its hyperparameters tuning to reduce overfit (Ojugo, Odiakaose, Emordi, Ako, et al. , 2023; Ojugo, Odiakaose, Emordi, Ejeh, et al. , 2023; Omoruwou et al. , 2024) as in Equation 2, where normfi is the normalized feature importance for *i* in tree j; While, Table 3 shows the Random Forest model design configuration (Geteloma et al. , 2024b, 2024a; Okofu, Akazue, et al. , 2024; Okofu, Anazia, et al. , 2024).

$$normfi_i = \frac{fi_i}{\sum_{j \in all\ features} fi_j} \quad Equation\ 2$$

Table 3. Random Forest Configuration

Features	Value
nEstimators	150
learnRate	0.25
maxDepth	5
minSampleSplit	10
randomState	25
evalSet	x,val, y_val

3. **AdaBoost** leans on the gradient boost mode (Ojugo & Otakore, 2018) – combining weak base learners to yield an optimal fit. It extends its objective function via minimized loss factor, which helps it control its decision trees' complexity – and combines the predictive processing such that each base learner strengthens the Adaboost as a stronger model (Yoro & Ojugo, 2019) for the training data x_i and its corresponding y_i. To enhance its performance as in Table 4, AdaBoost localizes the loss function $l(Y_i^t, \hat{Y}_i^t)$, fusing it with its regularization term $\Omega(f_t)$ as in its goal function. While, loss function devoid model of overfit, regularization allows train data to fit well irrespectively of model complexity to yield high accuracy (Yoro, Aghware, Akazue, et al. , 2023; Yoro, Aghware, Malasowe, et al. , 2023; Yoro & Ojugo, 2019) as in Equation 3.

$$\hat{Y}_i^t = \sum_{k=1}^{t} f_k(x_i) = \hat{Y}_i^t + f_k(x_i) \qquad (3)$$

Table 4. AdaBoost model Configuration

Features	Value
nEstimators	250
learnRate	0.25
maxDepth	5
randomState	25
evalSet	(x,val, y_val)

4. **Stacked XGB meta-learner** scales the gradient boost, and yields a stronger learner by aggregating its base (i.e. Decision tree, Random Forest and Adaboost) models via majority vote over a set of iterations. To effectively manage tree complexity for improved optimality, its base learners contribute to its knowledge about a task with each tree trained on the task dataset. To yield improved generalization, it ensures that training dataset are re-calibrated to remain within its solution's boundaries using tuned parameters for higher accuracy (Akazue, Edje, et al. , 2024; Akazue, Yoro, et al. , 2023). The XGBoost meta-learner design configuration is as in Table 5.

Table 5. XGBoost Meta-learner Design

Features	Value
nEstimators	250
learnRate	0.25
maxDepth	5
randomState	25
evalSet	(x,val, y_val)
evalMetric	["error', 'logloss']

Step 7 – Training and Validation: Trees as iteratively constructed to ensures the collective knowledge is used in identifying fibromyalgia symptoms (Eboka, Aghware, et al. , 2025) – where training blends synthetic with original data to guarantee improved learning and adaptability to variety of settings (Kumar et al. , 2025; Onoma, Agboi, Ugbotu, et al. , 2025). This helps the ensemble to quickly identify intricate outliers, present in dataset even with synthetic samples. This improves flexibility. The hyperparameter tuning controls how much of the tree's complexity and nodal weights need to be adjusted with gradient loss. A lower value means slower travel downward – ensuring how quickly a tree abandons old beliefs for new ones during training. As each tree learns, it identifies crucial (and unimportant) vitals as symptoms in the dataset. A higher learn rate means that our ensemble changes quickly as it learns newer features (Ojugo et al. , 2021a, 2021b). In addition – its regularization terms ensures all learned changes quickly impact its outcome, by carefully tuning its maxDepth, n_estimator, learnRate, and booster parameters (Cheng & Haw, 2023) for optimal performance (Ojugo, Odiakaose, Emordi, Ejeh, et al. , 2023). Validation with 25 percent of training data, estimates how well ensemble performs on test data using a fold (k=10) that

rearranges each fold to yield a good representation (Raza et al. , 2024) to devoid the ensemble of overfit.

3. RESULT FINDINGS & DISCUSSION

3.1. Performance Evaluation

Table 6 shows the performance evaluation for all learners (Decision Tree, Random Forest, and AdaBoost) respectively with the XGBoost meta-learner. It shows that our base-learners – both the Adaboost and Decision Tree underperformed in comparison to the Random Forest. However, all 3-base leaners yield Accuracy of 0.9815, 0.9968, 0.9981 for (DT, Adaboost and RF) respectively; Recall of 0.9745, 0.9848, and 0.9881 respectively; Precision of 0.9805, 0.9318, and 0.9541; And, F1 of 0.9805, 0.9881, and 0.9925 respectively. Conversely, the meta-learner yields perfect scores for its Accuracy, Recall, Precision, and F1 respectively.

Table 6. XGBoost meta-learner

Learners	Accuracy	Precision	Recall	F1
Decision Tree	0.9815	0.9805	0.9745	0.9805
AdaBoost	0,9968	0.9318	0.9848	0.9881
Random Forest	0.9981	0.9541	0.9881	0.9925
Meta-Learner				
XGBoost	1.0000	1.0000	0.9999	1.0000

Our XGBoost reduces the outcome relations conflict caused by computational complexities and diversity of the dataset; And also, devoid the ensemble of overfit due to the base-learners. Thus, our ensemble classifies fibromyalgia data accurately as detected dataset and has proven to efficiently reduce bias and variance as in the confusion matrix of Figure 5 – yielding a more stable, robust model for new data even with hidden underlying parameters. The study supports that SMOTE-ENN had great influence in resolving data imbalance for ground truth; Which in turn, impacted the overall performance by identifying features of importance that influence model prediction.

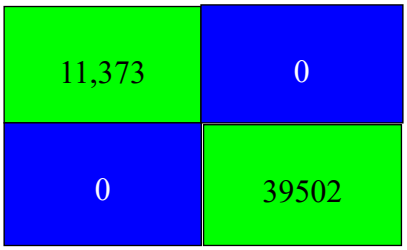

Figure 5. Confusion Matrix

3.2. Comparison / Benchmarking

As we explore the high performance of our proposed stacking ensemble across the domain dataset to demonstrate its flexibility, adaptability, robustness, and prediction ability – we also benchmark it against previous methods that have utilized the same or similar dataset. To this end – we found none (Ojugo & Yoro, 2020). Thus, we benchmark our ensemble against similar design constructs on various datasets for various domain tasks as seen in Table 8 (Oyemade & Ojugo, 2021). Medical domain task often proves to be more painstaking, and require that the chosen ensemble design metric must be strongly impacted by the consequence of diagnostic errors within the captured dataset, as these are directly related to the patient clinical outcomes (Geteloma et al. , 2024a).

Table 7. Ablation Studies / Benchmark

Learners	Accuracy	Precision	Recall	F1
(Allan-Blitz et al. , 2024)	0,9968	0.9318	0.9848	0.9881
(Karacaoglu et al. , 2024)	0.7824	0.7631	0.7500	0.7732
(Zetterman et al. , 2024)	1.0000	1.0000	0.9999	1.0000
(Ghasemieh et al. , 2023)	0.8728	0.8500	0.8120	0.8925
(Ako et al. , 2025)	0.9981	0.9541	0.9881	0.9925
(Akazue, Debekeme, et al. , 2023)	0.7815	0.7025	0.7372	0.7902
Our Method	1.0000	1.0000	0.9999	1.0000

5. CONCLUSION

This study implements a robust stacked ensemble targeted at fibromyalgia classification – fusing the predictive capabilities of DT, RF, and AdaBoost as base-learners with the XGBoost meta-learner. It

utilized SMOTEENN to resolve the imbalanced nature of the dataset and relief ranking feature selection to help yield fewer predictors that are of greater significance to ensure a fastened model construction and training. Despite the large dataset, the stacked ensemble successfully utilized SMOTEENN-fused XGBoosted ensemble to yield enhanced performance generalization; And its findings implies that the ensemble approach with such a robust XGBoost meta-regressor/learner does efficiently minimize the weaknesses inherent each of the explored base-learners – emphasizing the importance of a hybrid approach to identify, classify, and detect fibromyalgia symptoms (even with the inconsistent variance and bias in the dataset) especially as rippled across a variety of medical datasets. So, for the future of early disease identification and classification, this pilot study is a positive step and should be improved upon.

Conflict of Interest

The authors declare that there is no conflict of interest.

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