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Transforming Fibromyalgia Management: A Systematic Review of AI & ML Driven Approaches

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Abstract

Background: Fibromyalgia (FM) is a chronic disorder characterized by widespread pain, fatigue, poor sleep, and cognitive impairment. Because its symptoms overlap with those of many other conditions, FM is often underdiagnosed or misdiagnosed. Recent advances in artificial intelligence (AI) and machine learning (ML) offer promising tools to improve diagnosis by identifying objective physiological and neurobiological markers.

Methods: A systematic search was conducted in PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar following PRISMA 2020 guidelines. Of

471 records screened, 22 full-text articles were assessed and 12 met the inclusion criteria. Studies involving human FM populations and applying AI/ML methods for diagnosis, prediction, clustering, or biomarker discovery were included. Extracted data covered imaging modalities, feature-engineering approaches, validation strategies, and model performance.

Results: Across all included studies, AI/ML models outperformed conventional diagnostic approaches. Structural and resting-state MRI-based models, particularly support vector machines, feature-selection pipelines, and graph-based deep-learning approaches, achieved accuracies of 90–96% in identifying alterations in pain-processing and affective-regulation networks. Sleep-EEG and ECG-based models using nonlinear dynamics, entropy-based features, and quantum-inspired feature extraction frequently reported sensitivities and specificities around 90%. Other modalities, including retinal OCT, fNIRS, and musculoskeletal ultrasonography, also showed promising discriminative potential. However, most studies were limited by small sample sizes, inconsistent preprocessing methods, and lack of external validation, reducing clinical generalizability.

Conclusions: AI-assisted analysis of neuroimaging, electrophysiological, and musculoskeletal data offers a promising pathway for faster and more objective FM diagnosis. Larger datasets, standardized methods, explainable AI, and prospective validation are needed before routine clinical implementation.

Keywords: Fibromyalgia; artificial intelligence; machine learning; neuroimaging; chronic pain; diagnostic modelling.

Introduction

Two to three percent of the overall population suffers from fibromyalgia (FM), a non-inflammatory chronic pain disorder [1]. Fibromyalgia is a syndrome with a wide variety of symptoms that often accompany symptoms of other diseases. Patients who have fibromyalgia usually have psychological symptoms along with physical pain, including worry, sadness, insomnia, fatigue, alexithymia, and difficulty in performing daily activities. [2, 3]

While their opaqueness is a significant hurdle to their seamless entry into medical practice, artificial intelligence and machine learning [AL/ML] models have now been useful tools in guiding clinical judgments [4].In order to address this issue, the emerging discipline of explainable AI (XAI) aims to provide physicians with clear, data-backed information so they can make individualized, trustworthy diagnoses and treatments. Additionally, XAI makes it easier for doctors, patients, developers, and health regulators to work together to create and improve AI-based clinical decision support systems. [5]. AI/ML has been used to improve FM diagnosis and identify particular patient subgroups by using sophisticated classification models[6]. These models make use of a variety of data sources, such as neuroimaging, psychosocial variables, and patient-reported outcomes [7,8,9]. Several studies have used XAI approaches to investigate feature importance in model output. [10,11]. Although psychological factors (anxiety, depression, trauma) have emerged as pivotal predictors of FM severity, the interplay between pain perception and mental health status remains understudied [11,12]. Estimating the relative contributions of such factors could yield novel information with which to manage FM, giving rise to significant controversy amongst FM community members, with implications for directions for disease control.

Other than AI driven approaches these are some approaches for management of FM: In 2017, the European Alliance of Associations for Rheumatology

(EULAR) revised its recommendations for fibromyalgia management based on evidence from high-quality reviews and meta-analyses. Non-pharmacological therapies like aerobic exercise and strength activities should come after patient education as first treatment. They may be used in conjunction with other therapies like mindfulness-based stress reduction, massage, acupuncture, hydrotherapy, cognitive behaviour treatment, and contemplative movement therapies. Pharmacological therapies, including opioid analgesics, antidepressants, and anti-epileptic medications, constitute second-line treatment by both virtue of effectiveness as well as risk. They are reserved for refractory pain (e.g., amitriptyline, cyclobenzaprine, pregabalin) or insomnia (e.g., duloxetine, pregabalin, tramadol).The non-pharmacological intervention described contains a therapeutic coaching program, a cell phone application, as well as a wristband, in accordance with EULAR recommendations. Millimetre waves (MMW) released by the bracelet stimulate cutaneous nerve endings, reducing symptomatically [13]. The specific aim of this systematic review is to critically assess and review all available literature on the use of artificial intelligence (AI)/machine learning (ML) in diagnosing, classifying, and managing cases of fibromyalgia. More specifically, this particular research review will assess both its ability to diagnose efficiently across various imaging modalities, biomarkers, feature engineering approaches, and the use of multimodal approaches of explainable AI. It will also assess its methodological qualities along with their associated risks of bias. The final aim of such an investigation will reveal its importance for public health and clinical medicine in terms of improving its ability to diagnose efficiently.

Materials and Method:

Search Strategy

A systematic search was performed in:

- PubMed
- Scopus
- Web of Science
- IEEE database
- Google Scholar

Search terms included combinations of: “fibromyalgia”, “chronic pain”, “artificial intelligence”, “machine learning”, “deep learning”, “neural network”, “support vector machine”, “MRI”, “fMRI”, “biomarkers”, “digital health”, and “predictive modelling”. The search period was from 2010 to till date

The review followed PRISMA 2020 guidelines.

Inclusion Criteria

- Human studies involving adults with fibromyalgia
- Research applying AI/ML models for diagnosis, prediction, biomarker discovery, digital therapy, or clustering
- Randomized trials, cohort studies, cross-sectional studies, and secondary analyses
- English-language full-text articles

Exclusion Criteria

- Animal studies
- Studies without AI/ML components
- Reviews, protocols, editorials
- Insufficient methodological reporting

Results

The table 1 represents Characteristics of Included Studies Applying AI and Machine Learning in Fibromyalgia, the table 2 represents Summary of Key Outcomes and Performance Metrics of AI- and ML-Based Studies in Fibromyalgia and the table 3 represents risk of bias for the included studies was independently assessed using the Office of Health Assessment and Translation

(OHAT) Risk of Bias Tool across six domains: selection bias, detection bias, attrition/exclusion bias, confounding bias, selective reporting bias, and other potential sources of bias. Each domain was rated as definitively low risk (++), probably low risk (+), probably high risk (–), or definitively high risk (--). Based on the overall bias assessment presented in Table 3, a heterogeneous quality profile is observed across the included studies. Several investigations namely Vipul Yadav et al. (2025), Marchesoni et al. (2022), L. Sevel et al. (2024), Gökçay et al. (2018), Fallon et al. (2020), and Callan et al. (2014) were classified as having a probably high risk of bias, largely attributable to issues related to selection methods, confounding factors, or limited validation strategies. A smaller subset of studies, including Muhammad Armughan Ali et al. (2017), Prabal Datta Barua et al. (2023), Michael Behr et al. (2020), and Liang et al. (2023), demonstrated a definitively high risk of bias, reflecting significant methodological limitations such as small sample sizes, inadequate control of confounders, or absence of external validation. In contrast, several studies Nguyen Thanh Nhu et al. (2022), Paul et al. (2019), Boquete et al. (2022), Labus et al. (2015), Robinson et al. (2015), Ung et al. (2014), Sundermann et al. (2014), and Aiden Rushbrooke et al. (2023)were judged to have a probably low risk of bias, suggesting acceptable internal validity despite minor limitations. Importantly, Martin-Brufau et al. (2021), Bagarinao et al. (2014), and Lopez-Sola et al. (2016) exhibited a definitively low risk of bias, indicating stronger study design and methodological rigor. Overall, this distribution highlights a gradual improvement in study quality over time while underscoring the need for larger, well-controlled, and externally validated AI-based studies in fibromyalgia research

Figure 1: PRISMA 2020 flow diagram for newly conducted systematic reviews that solely involved database and registration searches

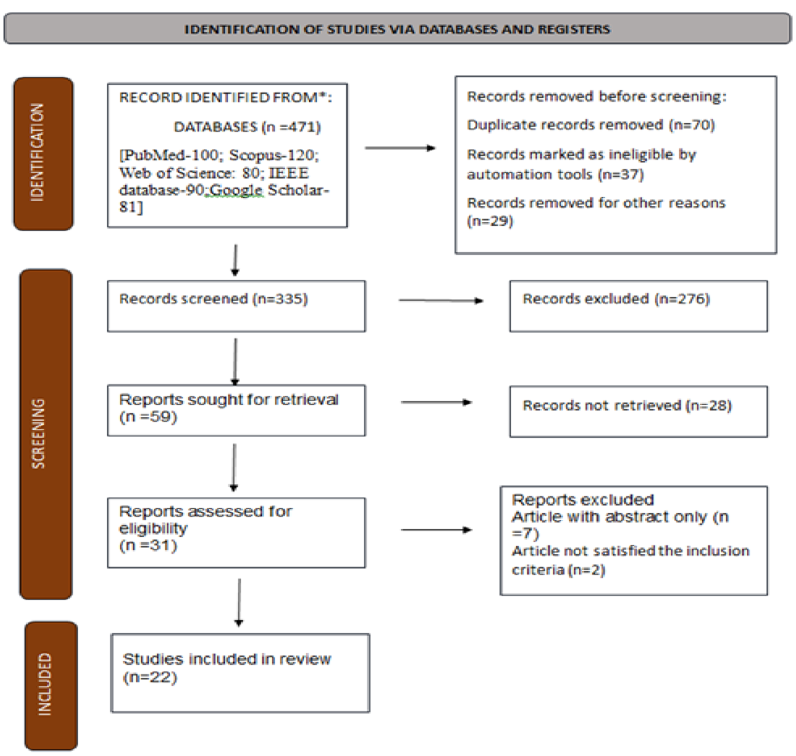

Table 1: Characteristics of Included Studies Applying AI and Machine Learning in Fibromyalgia

Sn.	Author Year	Imaging used	Prediction method	Intervention
1.	Vipul Yadav et al. 2025 [16]	X-ray, CT scan, MRI, EMG (used to exclude other diseases)	Machine Learning: Support Vector Machines (SVM), K-Nearest Neighbor (K-NN)	Holistic treatment: medication, physiotherapy, psychotherapy, yoga, meditation, exercise, patient education
2.	Marchesoni A. et al. 2022 [17]	Ultrasonography Gray Scale [GS] & Power Doppler [PD]	Multivariate logistic regression, ROC analysis, and Principal Component Analysis (PCA)	Clinical and ultrasound assment of entheseal sites in PsA vs FMS patients (post-hoc analysis of ULISSE study)
3.	Muhammad Armughan Ali, et al. 2017 [18]	Musculoskeletal ultrasound (MSKUS)	Clinical symptoms + MSKUS findings	Leflunomide → Methotrexate + Mycophenolate → Etanercept 50mg weekly (final effective treatment)
4.	Nguyen Thanh Nhu et al. 2022 [19]	Resting-state functional MRI (rs-fMRI) and structural MRI	Machine Learning (ML) using recursive feature elimination (RFE) + permutation importance, classifiers: SVM, LR, etc.	Not an interventional study – observational classification study
5.	L. Sevel et al. 2024 [20]	Structural MRI (sMRI)	Machine Learning: LASSO, SMO-SVM, LIBSVM, J48decision tree, Naïve Bayes with leave-one-out cross-validation using RapidMiner	None (observational study)
6.	a. Paul et al. 2019 [21]	ECG	Nonlinear features, entropy, energy, power, Student's t-test, SVM	Sleep stage 2 and 3 ECG sleep signal analysis
7.	Martin-Brufau et al. 2021 [22]	ECG	Fourier transformation, band power, coherence analysis, t-test, discrimination index	Band analysis from 23 FM and 23 HC subjects
8.	Gökçay et al. 2018 [23]	FNIRS	Functional connectivity matrices, PCA, t-test, fusion of kNN, SVM, LDA classifiers	Functional near-infra red spectroscopy imaging of 19 FM and 16 HC patients
9.	Thanh Nhu et al. 2022 [24]	MRI	Gray matter matrix, recursive feature elimination, PCA, SVM, logistic regression, kNN, etc.	MRI of 26 FM and 30 HC subjects
10.	Boquete et al. 2022 [25]	OCT (retina)	Retinal layer analysis, RUSBoost, statistical tests	OCT of 29 M and 32 HC subjects

11.	KarabeyAksalli I et al. 2023 [26]	Sleep EEG (Polysomnography)	Machine Learning Classifiers including: SVM, KNN, Random Forest, Naïve Bayes; Feature extraction using nonlinear dynamical methods (bispectrum, entropy, fractal features)	No clinical intervention; EEG recorded during natural sleep
12.	Bagarinao et al. 2014 [27]	Structural MRI (VBM)	Supportive Vector Machine (SVM)	Electrical pain induction
13.	Labus et al. 2015 [28]	Structural MRI (thickness, curvature, area)	Spares partial least squares-discriminant analysis (sPLS-DA)	Electrical pain induction
14.	Robinson et al. 2015 [29]	Structural MRI	LR, MLP, Bayes, SVM. Decision Tree (J48)	Electrical pain induction
15.	Ung et al. 2014 [30]	Structural MRI (GM density)	Support Vector Machine(SVM)	Electrical pain induction
16.	Callan et al. 2014 [31]	FMRI (pain stimulation)	Sparse Logistic Regression (SLR)	Electrical pain induction
17.	Sundermann et al. 2014 [32]	Resting-state FMRI	SVM, k-Nearest Neighbors (kNN)	Electrical pain induction
18.	Lopez-sola et al. 2016 [33]	FMRI (multisensory tasks)	SVM, Logistic regression (LR)	Painful pressure & multisensory stimuli
19.	Barua et al. 2023 [34]	ECG signals (single-lead, during seep stage 2 & 3)	Quantum-inspired 3LBP feature extractor - Multilevel Discrete Wavelet Transform (MFMDWT) - Feature Selection: Chi-square &Neighborhood Component Analysis (NCA) - Classification: Support Vector Machine (SVM), k-Nearest Neighbors (kNN) - Validation: Leave-One-Record-Out (LORO) cross-validation - Information Fusion: Iterative Majority Voting (IMV)	No physical/clinical intervention – analysis of pre-recorded ECG data (16 fibromyalgia + 16 control subjects)
20.	Michael Behr et al. 2020 [35]	B-mode Ultrasound	Support Vector Machine (SVM), Logistic Regression with Elastic Net Regularization	Texture feature extraction from upper trapezius ultrasound images of FM and healthy subjects using MATLAB; models trained and

				validated with nested cross-validation
21.	Liang et al. 2023 [36]	Resting-state Functional Magnetic Resonance Imaging (rs-fMRI)	Fused Brain Functional Connectivity Network (BFCN) combined with Graph Convolutional Network (GCN) using Edge Attention Mechanism	rs-fMRIdatafrom 172 female subjects (86 FMS, 86 controls); features from 116 brain regions (AAL atlas); integration of imaging and non-imaging data (e.g., age)
22.	Aiden Rushbrooke et al. 2023 [37]	Electrocephalography (ECG)	Machine learning and AI-based Time Series Classification (TSC) methods — including ROCKET, MiniROCKET, MultiROCKET, FreshPRINCE, HIVE-COTEv2, InceptionTime, DrCIF, TDE, and 1NN-DTW; models assessed performance on multivariate EEG datasets without handcrafted features	Application of ML classifiers directly on EEG signals from multiple datasets and on a new Fibromyalgia Syndrome (FMS) EEG study; no manual feature engineering was performed

Table 2: Summary of Key Outcomes and Performance Metrics of AI- and ML-Based Studies in Fibromyalgia

Sn.	Author Year	Result	Outcome
1.	Vipul Yadav et al. 2025 [16]	ML model achieved 96.77% accuracy using SVM and K-NN on test data	Developed a web-based ML tool to assist diagnosis and treatment planning, with potential clinical use cases
2.	Marchesoni A. et al. 2022 [17]	GS abnormalities more frequent in PsA (90%) than FMS (62.7%). GS Score > 3.5 best differentiated PsA (sensitivity 75%, specificity 63%). Achilles and proximal patellar enthesitis strongly associated withPsA. PD lea discriminatory (AUC = 0.657).	Ultrasound helps differentiate PsA from FMS, especially with multiple GS-mode abnormalities. PD finings less specific.
3.	Muhammad Armughan Ali, et al. 2017 [18]	Initial misdiagnosis as FMS and osteoarthritis. MSKUS revealed low-grade synovitis, tendonitis, enthesitis. Etanercept led to CRP drop (1.36 → 0.64 mg/dL), symptom resolution.	Accurate diagnosis of seronegative RA; effective disease control with Etanercept. Highlights utility of MSKUS in distinguishing RA from FMS.
4.	Nguyen Thanh Nhu et al. 2022 [19]	rs-FC model: Accuracy = 0.91, AUC = 0.93; Structural model: Accuracy = 0.86, AUC = 0.88; Combined model: Accuracy = 0.95, AUC = 0.95	rs-FC and structural MRI features can effectively differentiate fibromyalgia patients from healthy controls. rs-FC outperforms structural MRI in prediction. Combined features perform best.
5.	L. Sevel et al. 2024 [20]	SR and sMRI both performed well in distinguishing patients from healthy controls (SR	ML-sMRI features can accurately distinguish FM and CFS patients; FM showed hypertrophy, CFS

		= 89.66%, sMRI= 81.03%, p=0.25);sMRI outperformed SR in distinguishing CFS vs FM (sMRI= 90.83%, SR = 47.50%, p<0.001)	atrophy in key regions
6.	a. Paul et al. 2019 [21]	Stage 2: Acc 96.15%, Sens 96.88%, Spec 95.65%; Stage 3: Acc 84.85%, Sens 89.66%, Spec 81.08%	Demonstrated the viability of using EEG for fibromyalgia detection
7.	Martin-Brufau et al. 2021 [22]	AUC 61.80–98.80%; Sensitivity 64.30–100%	Showed high potential of EEG analysis for FM characterization
8.	Gökçay et al. 2018 [23]	Sensitivity and specificity up to 100%depending on classifier fusion	fNIRS proved effective for FM detection under optimized classifier conditions
9.	Thanh Nhu et al. 2022 [24]	Accuracy 95% Sensitivity 96% Specificity 93%	MRI-based model showed strong FM classification capability
10.	Boquete et al. 2022 [25]	Accuracy 82% Sensitivity 86% Specificity 78%	Demonstrated potential of retinal imaging in FM detection
11.	KarabeyAksalli I et al. 2023 [26]	Nonlinear dynamical EEG features (especially during NREM sleep) significantly differentiated fibromyalgia patients from controls	Highest model accuracy reached ≈ 97% (depending on feature set + classifier), showing ML can reliably classify FM using sleep EEG patterns
12.	Bagarinao et al. 2014 [27]	Accuracy:73% Sensitivity: 70% Specificity: 73%	ML could differentiate chronic pelvic pain from healthy controls
13.	Labus et al. 2015 [28]	Accuracy:70% Sensitivity: 65% Specificity: 75%	Identified morphology signatures distinguishing IBS from controls
14.	Robinson et al. 2015 [29]	Accuracy:76% Sensitivity: 81% Specificity: 75%	Brain volumes provided moderate accuracy; self-report data performed better
15.	Ung et al. 2014 [30]	Accuracy:76% Sensitivity: 76% Specificity: 75%	Structural changes distinguished cLBP from controls
16.	Callan et al. 2014 [31]	Accuracy:92% Sensitivity: 92% Specificity: 92%	High accuracy classifier for Clbp using MRI activation data
17.	Sundermann et al. 2014 [32]	RA vs HC: 79%, FM vs HC: 62%, RA vs FM: 79%	Functional connectivity-based classification of FM and RA
18.	Lopez-sola et al. 2016 [33]	Accuracy:93% Sensitivity: 92%	Discriminated FM from HC with high accuracy using sensory brain signatures

		Specificity: 94%	
19.	Barua et al. 2023 [34]	Stage 2 Accuracy: 93.87% - Stage 3 Accuracy: 92.02% - Sensitivity: Up to 99.41% - Specificity: Up to 97.39%	ML/AI model successfully differentiated fibromyalgia ECGs from healthy ones with high accuracy; the model is lightweight, self-organizing, and clinically implementable
20.	Michael Behr et al. 2020 [35]	SVM: 83.9% ± 2.6% accuracy (predicted), 84.1% (test set) - LR: 65.8% ± 1.7% accuracy (predicted), 66.0% (test set) - SVM outperformed LR significantly ($p < 0.0001$)	SVM successfully discriminated FM from healthy muscle with clinically relevant accuracy; demonstrated potential as an objective diagnostic tool for FM
21.	Liang et al. 2023 [36]	Accuracy: 82.48%; Sensitivity: 84.58%; Specificity: 80.13%; AUC: 82.36%	The fusion of Pearson's correlation–based and low-rank BFCNs, coupled with edge-attention GCN, significantly enhanced fibromyalgia classification accuracy. This approach effectively identifies disease-related brain connectivity patterns and supports early, computer-aided diagnosis
22.	Aiden Rushbrooke et al. 2023 [37]	ROCKET-based classifiers (MiniROCKET, ROCKET, Arsenal) achieved the highest accuracy across datasets; performance matched or exceeded traditional feature-based models in most EEG datasets; for FMS data, Theta and Alpha frequency bands were most discriminative	Demonstrated that machine learning time-series models can accurately classify EEG data without dataset-specific preprocessing; validated the effectiveness of AI in detecting neurological differences (e.g., FMS indicators) and supported EEG as a viable domain for generalized ML-based classification

Table 3: Risk of Bias Assessment of Included Studies Using the OHAT Tool

Sn.	Author Year	Detection Bias	Selection Bias	Attrition Bias	Confounding Bias	Selective Reporting Bias	Other Bias	Overall Bias
1.	Vipul Yadav et al. 2025 [16]	++	-	++	-	-	-	-
2.	Marchesoni A. et al. 2022 [17]	+	-	++	--	-	-	-
3.	Muhammad Armughan Ali, et al. 2017 [18]	++	-	++	--	--	--	--
4.	Nguyen Thanh Nhu et al. 2022 [19]	++	+	++	-	-	-	+
5.	L. Sevel et al. 2024 [20]	++	-	++	-	--	--	-
6.	a. Paul et al. 2019 [21]	+	+	++	++	+	+	+

7.	Martin-Brufau et al. 2021 [22]	++	+	++	++	++	+	++
8.	Gökçay et al. 2018 [23]	–	––	–	++	–	–	–
9.	Thanh Nhu et al. 2022 [24]	++	+	++	+	++	+	+
10.	Boquete et al. 2022 [25]	+	+	–	++	+	+	+
11.	KarabeyAksalli I et al. 2023 [26]	++	-	++	-	-	-	-
12.	Bagarinao et al. 2014 [27]	++	++	++	++	++	++	++
13.	Labus et al. 2015 [28]	+	+	++	++	+	+	+
14.	Robinson et al. 2015 [29]	++	+	++	+	+	+	+
15.	Ung et al. 2014[30]	+	–	++	++	+	+	+
16.	Callan et al. 2014[31]	–	–	++	+	–	––	–
17.	Sundermann et al. 2014 [32]	+	–	++	+	+	+	+
18.	Lopez-sola et al. 2016 [33]	++	+	++	++	+	+	++
19.	Barua et al. 2023 [34]	++	-	++	--	--	--	--
20.	Michael Behr et al. 2020 [35]	+	-	+	--	-	--	--
21.	Liang et al. 2023 [36]	++	--	++	--	-	--	--
22.	Aiden Rushbrooke et al. 2023 [37]	++	+	++	+	+	+	+

Note:

++	Definitively low risk
+	Probably low risk
-	Probably high risk
--	Definitively high risk

Discussion

Recent studies have shown the increasing importance of ML and AI in the diagnosis and distinction of FM from related disorders using various imaging modalities. Logistic regression and SVM models exhibited good diagnosis accuracy in distinguishing FM from inflammatory diseases such as psoriatic or rheumatoid arthritis using musculoskeletal ultrasonography and ultrasound. Integrating multimodal data further improves the performance of deep learning techniques, as well as ensemble models, in fMRI or retinal OCT data. For example, based on musculoskeletal ultrasonography, logistic regression, support vector machines, or SVM, among others, have shown excellent discriminatory ability for distinguishing FM from other disorders like psoriatic or rheumatoid arthritis. Using a combination of structural and resting-state data, MRI-based approaches have identified unique brain morphology and connectivity patterns in FM patients, yielding high diagnostic accuracies of over 90% using methods such as SVM, recursive feature elimination, and graph convolutional networks. Non-invasive FM detection has also been validated by reports of high sensitivities and specificities using modern classifiers applied to fNIRS, EEG, and ECG signals. Yadav et al.[16] (2024–2025) achieved a high level of accuracy of 96.77% to classify cases related to fibromyalgia with the ability to combine X-rays, CT scans, MRI scans, and EMG scans to form the SVM and K-NN classifiers. Therapy, yoga, psychology therapy, and patient education sessions have been considered for comprehensive patient care in this work. Their recommendations for treatment and diagnosis of the condition were verified by the internet-based machine learning assistance platform. In a post-hoc analysis of the ULISSE trial, Marchesoni et al.[17] used greyscale and power Doppler ultrasound to characterize differences between fibromyalgia syndrome (FMS) and psoriatic arthritis (PsA). Greyscale abnormalities were found to be significantly higher in PsA than in FMS, at 90% vs. 62.7%, respectively, with a cut-off greyscale severity >3.5 being most sensitive (75%) but having moderate specificity (63%). Enthesitis at both Achilles' tendons and proximal patella was highly sensitive for PsA, but power Doppler was not highly specific. Nonetheless, this study shows that greyscale ultrasound scanning can accurately differentiate between PsA and FMS. Ali et al.[18] demonstrated musculoskeletal ultrasonographic differences between seronegative rheumatoid arthritis, fibromyalgia, and osteoarthritis based upon low-grade synovitis, tendinitis, and enthesitis. MSKUS-directed treatment resulted in appropriate etanercept therapy with subsequent clinical and CRP response, emphasizing its role in the diagnosis of unusual cases of RA. Nguyen et al.[19] (2022**)** assessed the classification accuracy of resting-state functional MRI and structural MRI using ML for fibromyalgia diagnosis. Resting-state functional MRI was superior to structural MRI (AUC: 0.93 vs. 0.88), but a multi-modal classification model incorporating SVM and logistic regression showed superior results than all other models (AUC: 0.95) to differentiate fibromyalgia patients from healthy controls. Sevel et al.[20] (2023–2024) demonstrated the ability to distinguish fibromyalgia patients, CFS patients, and healthy controls using machine learning in the analysis of structural MRI, and surface-based MRI performed better than conventional MRI in distinguishing between FM patients and CFS patients (90.83% vs. 47.50%, $p < 0.001$). Hypertrophic and atrophied regions in FM and CFS, respectively, indicate the ability to use machine learning in distinguishing between the conditions.

Recent research has used the incorporation of physiological and neuroimaging characteristics through machine learning for the improved classification of fibromyalgia patients. Aksalli et al.[26] (2023) used the near-perfect classification results with the aid of ECG signals from varying phases of sleep through the use of sophisticated classifiers and the GluPat FE algorithm. High levels of classification accuracy were recorded by Paul et al.[21] (2019) and Martin-Brufau et al.[22] (2021) using EEG signals with AUC values between 61.8% and 98.8%, and sensitiveness up to 100%. Gokcay et al.[23] (2018) used fNIRS with functional connectivity and classifier fusion techniques and recorded specificities and sensitivities of up to 100%. MRI classification systems by Thanh Nhu et al.[24] (2022) showed 95% accuracy and 96% sensitivity, while the OCT retinal imaging method by Boquette et al. [25] (2022) showed 82% accuracy. MRI-Based Structural and Functional Machine Learning Techniques: Structural MRI and machine learning analysis have been employed for the detection of the corresponding biomarkers for chronic pain within the brain. Bagarinao et al.[27] (2014) predicted chronic pelvic pain with a 73% accuracy using SVM on MRI, which implicated the hippocampus, amygdala, pre-supplementary motor area, and primary somatosensory cortex, among others. Labus et al.[28] (2015) provided 70% accuracy, 65% sensitivity, and 75% specificity using sPLS-DA on sMRI for the classification of IBS, and Robinson et al.[29] (2015) provides MRI-based ML accuracy 53-76%, best feature -left amygdala, d=.66 vs Self-report ML accuracy 79-96% (mood), 83-96% (pain); anger d 1.83, pain d 2.84 vs Conclusion Self-report accuracy ~ 22 %. whereas Ung et al.[30] (2014) again provided 76% accuracy, 75% sensitivity, and specificity using SVM for grey matter density to detect chronic low-back pain. Functional MRI classification performance was shown to be enhanced. High classification accuracy of 92% for both sensitivity and specificity was obtained by Callan et al. [31] Using sparse logistic regression for classifying pain-induced fMRI. Sundermann et al.[32] used SVM and kNN classification methods for identifying patients with rheumatoid arthritis and healthy individuals at 79%, patients with fibromyalgia and healthy individuals at 62%, and patients with rheumatoid arthritis and patients with fibromyalgia at 79%. López-Solà et al.[33] have shown the capability of FM classification using multisensory and pain fMRI responses with the accuracy of 93%, sensitivity of 92%, and specificity of 94%. Barua et al.[34] (2023) employed ECG during the different stages of sleep using the SVM and kNN classification methods along with bilayer wavelet transforms and quantum-inspired 3LBP, and their result remarkably classified patients with fibromyalgia and healthy participants. The iterative decision fusion technique not only consolidated the result but indicated the potential use of AI-based ECG for diagnosis. Machine learning applied to B-mode ultrasound imaging can successfully distinguish fibromyalgia sufferers from healthy controls, according to a study by Behr et al.[35] in 2020. SVM significantly outperformed logistic regression when textural information of the upper trapezius muscle was used, emphasizing the importance of classifier selection in prediction performance. Although more validation on bigger cohorts is needed, these results suggest that AI-driven analysis of muscle ultrasonography can function as an objective, non-invasive diagnostic adjunct for fibromyalgia. Liang et al.[36] (2023) have successfully proved that patients suffering from fibromyalgia can be classified accurately by using resting-state fMRI and graph-based machine learning methods. The model used edge attention GCNs and integrated functional connectivity graphs, which showed high levels of accuracy, sensitivity, and specificity. This study throws some light on the future prospects of AI-assisted neuroimaging that can be a fast, painless, and objective diagnostic technique for patients with fibromyalgia. The success of machine learning time series classification algorithms in the classification of fibromyalgia patient EEG signals was emphasized by Rushbrooke et al.[37] (2023). High accuracy was obtained without any need for human intervention in feature extraction by variants of the ROCKET algorithm. The most discriminative information is seen to be present in the Theta and Alpha bands of the signal, thereby implying that AI is capable of identifying any neurological disturbance due to fibromyalgia and that the diagnostic potential of EEG is not insignificant.

The range of care management strategies included in various research articles on fibromyalgia treatment follows a predominantly diagnostic inclination with implications for artificial intelligence/machine learning management methods. Vipul Yadav et al. (2025) took a distinctive stance by suggesting a comprehensive combination of pharmacological agents, physiotherapy, psychotherapy, exercise, yoga, meditation, and patient education, thus providing clinicians with tools for AI/ML management methods based on comprehensive, “multimodal” inputs by AI/ML algorithms from various sources such as reports from patients, psychological parameters, physical/vital parameters, etc., for dynamically managing treatment options for each patient, as suggested by various articles on fibromyalgia treatment. Similarly, pharmacological escalation therapy suggested by Muhammad Armughan Ali et al. (2017), including leflunomide, methotrexate, mycophenolate, etanercept, etc., for fibromyalgia treatment provides structured responses of drugs to treatment with AI/ML algorithms for taking care of patients but suffers from adverse effects of pharmacological agents on health status and the failure of such treatment modalities to incorporate supportive behavioral outputs from treatment for overall improvement of health status of patients with fibromyalgia. The pain induction methods developed by Bagarinao et al. (2014), Labus et al. (2015), Robinson et al. (2015), Ung et al. (2014), Callan et al. (2014), Sundermann et al. (2014), and López-Sola et al. (2016), among others, seem to have been designed for methodological development for validation of ML models using standardized pain induction methods for model validation purposes. Notwithstanding that, such methods are not clinically relevant to disease management for patients suffering from various diseases. In contrast, studies based on various imaging analyses such as MRI, fMRI, EEG, ECG, fNIRS, ultrasound, OCT, etc. (Nguyen Thanh Nhu et al., 2022; L. Sevel et al., 2024; Gökçay et al., 2018; Michael Behr et al., 2020; Boquete et al., 2022; Karabey Aksalli et al., 2023; Barua et al., 2023; Liang et al., 2023; Aiden Rushbrooke et al., 2023), among many others, offer vital information that is an indispensable requirement for the development of artificial intelligence or ML. From the perspective of the AI/ML technology, the holistic intervention in the view of Vipul Yadav et al. (2025) has come to acquire a place as a more preferable option in the context of the management and intervention in the case of fibromyalgia. The perturbability and variability in the case of fibromyalgia include a wide range of heterogeneities in the severity and intensity of the symptoms, the psychological characteristics, and the sleep and function factor. The scope for an ROI-driven decision-making system is thus less in the case of a holistic intervention—it is in this context that an effective AI/ML intervention platform becomes most pertinent for addressing the plausibilities involved in the optimized interrelation and interrelation between the intervention and the various parameters in the context wherein the intervention techniques provide a platform for the incorporation and the pursuit of a feedback-driven loop wherein the efficacies in the context of the intervention in the case of pharmacological factors and the intervention in the context of exercises and lifestyle factors falling under the broader umbrella of stimulus interventions.

AI and ML are of great public health importance in that they make it possible to diagnose fibromyalgia earlier and more accurately. Without a strong test marker, FM symptoms often overlap with those of other diseases, so many patients have no answers for years. In order to minimize this delay and ensure that patients get the proper care sooner, objective indicators can be provided through AI-supported analysis of imaging and physiological signals. Better quality of life, less frequent medical visits, and reduced long-term effects of chronic pain-this is possible with the increase in detection in routine clinical settings enabled by these technologies. The technologies also further equal and consistent diagnoses, especially in underprivileged areas. On a broader scale, population FM tracking can be improved by AI techniques to steer resource planning and health policy. Taking everything into consideration, AI/ML has helped make the public health response to fibromyalgia quicker, more equitable, and successful.

Conclusion

This systematic review demonstrates how AI and ML are becoming into effective tools for fibromyalgia diagnosis and treatment. AI models showed great accuracy and often outperformed traditional clinical assessment in a wide array of imaging modalities, including MRI, fMRI, ultrasonography, EEG, ECG, and even fNIRS. These systems may correctly differentiate fibromyalgia from healthy people and even from related disorders such as rheumatoid arthritis, chronic fatigue syndrome, and psoriatic arthritis. The best-performing models that incorporated a variety of data sources attested to the complexity of fibromyalgia, which encompasses both psychological and physical factors. Additionally, by identifying important patterns that are exclusive to each patient, AI has the potential to offer individualized treatment. To sum up, AI-based methods provide a non-invasive, objective means of improving fibromyalgia diagnosis and might improve clinical judgment. However, before these technologies can be fully adopted into routine medical practice, larger studies and established methodologies are needed.

Abbreviations

PRISMA—Preferred Reporting Items for Systematic Reviews and Meta-Analyses; SVM—Support Vector Machine; GCN—Graph Convolutional Network; EEG—Electroencephalography; ECG - Electrocardiography; fMRI—Functional Magnetic Resonance Imaging; fNIRS—Functional Near-Infrared Spectroscopy; OCT—Optical Coherence Tomography; CFS—Chronic Fatigue Syndrome; PsA—Psoriatic Arthritis; RA—Rheumatoid Arthritis; XAI—Explainable Artificial Intelligence; ULISSE: Refers to different research initiatives and projects, most notably in the fields of medicine and astronomy: rs-FC: resting state- Functional Connectivity; LASSO: Least Absolute Shrinkage and Selection Operator; SMO-SVM: Sequential Minimal Optimization-Support Vector Machine; LIBSVM: Library for Support Vector Machines; SR: Self Report; INCA: Iterative Neighbourhood Component Analysis; IChi2: Iterative Chi Square; LORO: Leave One Record Out; OCT: Optical coherence tomography; fMRI: functional magnetic resonance imaging.

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