Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 10 , October - 2026

An Interpretable Rule-Based Clinical Decision Support Framework for Electrotherapy-Related Conditions using Simulink

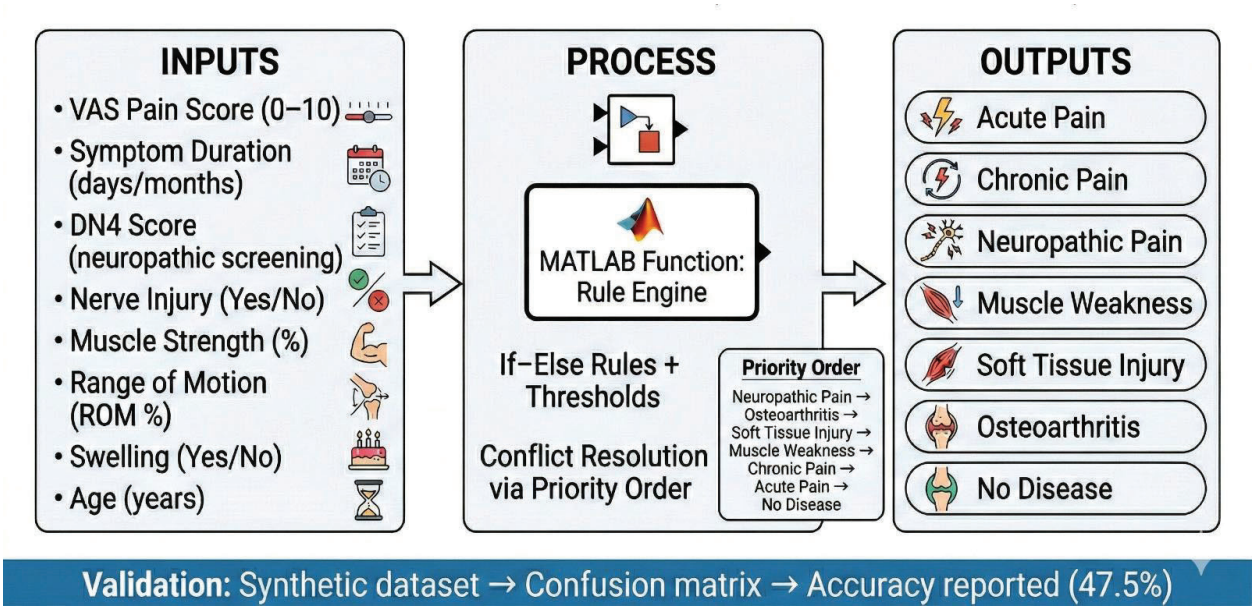
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GRAPHICAL ABSTRACT



Procedure of the suggested MATLAB/Simulink rule-based illness detection model. Clinical inputs (VAS, symptom duration, DN4, nerve damage, muscle strength, ROM and age) are analyzed by if–else threshold rules employing priority-based conflict resolution to categorize patients into seven electrotherapy-related diseases. Validation is demonstrated via a fake dataset and accuracy derived from a confusion matrix.

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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ABSTRACT

Electrotherapy techniques, including Transcutaneous Electrical Nerve Stimulation (TENS) and Neuromuscular Electrical Stimulation (NMES), are extensively utilized in physiotherapy for pain alleviation and musculoskeletal rehabilitation. Treatment selection frequently relies on expert clinical judgment, which may not be uniformly accessible across all healthcare environments. This research introduces a comprehensible, rule-based mathematical model for disease identification, executed in MATLAB/Simulink, to categorize clinical situations pertinent to electrotherapy. The model correlates validated clinical inputs—Visual Analog Scale (VAS), symptom duration, DN4 score, muscle strength percentage, range of motion (ROM), swelling, and age—into seven output categories: acute pain, chronic pain, neuropathic pain, muscle weakness, soft tissue injury, osteoarthritis, and absence of disease. The innovation of the approach is the explicit operationalization of clinically recognized criteria into transparent decision equations that can be simulated and audited within Simulink. A synthetic dataset was created to verify the rule logic. Through confusion-matrix-based evaluation, the model attained an overall accuracy of 47.5% on the synthetic dataset, suggesting that symptom overlap, and threshold closeness may result in misclassification inside deterministic rule systems. These findings validate the model as a proof-of-concept decision-support framework and encourage the modification of rule priorities and further validation using actual clinical datasets. This work presents a proof-of-concept framework validated on a synthetic dataset, intended for future clinical integration.

Keywords: Disease Detection, Electrotherapy, Mathematical Model, Simulink, Rule-Based System, Clinical Decision Support.

1. Introduction

Pain-related and musculoskeletal disorders represent a significant global health burden and are among the leading causes of disability worldwide [1], [2]. Accurate classification of patient conditions is essential for effective therapeutic planning and outcome improvement in rehabilitation and electrotherapy domains [3]. Clinical decision-making commonly relies on structured assessment parameters such as pain intensity, symptom duration, neurological screening scores, muscle strength evaluation, joint mobility, and age-related risk indicators [4], [5], [6], [7]. However, integrating these heterogeneous clinical indicators into consistent and reproducible diagnostic decisions remains challenging in routine clinical environments [8].

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The Visual Analog Scale (VAS) is widely validated for quantifying pain intensity and is routinely used in both acute and chronic pain assessment frameworks [4], [9] . Symptom duration is a critical diagnostic criterion, with chronic pain formally defined as pain persisting for three months or longer according to international classification standards [10]. Neuropathic pain identification is frequently supported by validated screening instruments such as the DN4 questionnaire, which demonstrates strong sensitivity and specificity in clinical populations[11]. Similarly, reductions in muscle strength and restricted range of motion are recognized indicators of functional impairment in musculoskeletal and rehabilitation medicine[12].

Decision-support systems have increasingly been adopted in healthcare to enhance diagnostic consistency and reduce subjectivity in clinical practice [13]. Rule-based expert systems, in particular, offer interpretability and transparency, aligning closely with traditional clinical reasoning processes[14]. Unlike purely data-driven black-box models, rule-based systems allow explicit incorporation of validated clinical thresholds derived from established medical literature[15]. Such transparency is especially important in healthcare applications where explainability and safety are primary concerns [16].

Computational modeling platforms such as MATLAB and Simulink are widely utilized in biomedical engineering research for system design, simulation, and performance evaluation under controlled conditions [17]. Simulation-based validation using structured datasets is an accepted preliminary evaluation approach when real-world clinical data are limited or restricted due to ethical considerations [18]. Therefore, the development of a structured rule-based mathematical model supported by validated clinical thresholds and evaluated using simulation techniques represents a methodologically justified approach for early-stage decision-support system design [14], [17].

Despite extensive clinical evidence supporting electrotherapy, the decision-making process for selecting appropriate treatment modalities remains largely manual and experience-based. This highlights the need for structured, interpretable, and automated decision support systems. In this work, a mathematical rule-based disease detector is developed and implemented in Simulink to classify electrotherapy-related conditions using clinically validated thresholds derived from the literature. The proposed system aims to bridge the gap between clinical knowledge and computational modeling.

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Notwithstanding substantial data endorsing electrotherapy, the process of clinical decision-making for the selection of suitable electrotherapy interventions predominantly relies on manual methods and experiential knowledge. In standard practice, clinicians must analyze various clinical signs (pain severity, duration, neuropathic assessment, muscle strength, range of motion, and) to ascertain the most probable underlying problem prior to selecting a treatment approach. This approach may become unreliable in the absence of professional physiotherapists or when documentation is deficient. Consequently, a structured and interpretable decision-support framework is required to transform proven clinical scales into clear, reproducible categorization logic appropriate for application in a simulation setting.

We opted for a rule-based approach instead of machine-learning technologies due to the transparency, auditability, and direct alignment with established clinical thresholds that rule-based systems offer. In initial phases where authentic labeled clinical datasets may be scarce, deterministic rule models facilitate swift prototyping, error identification, and clinician-friendly interpretation. Future research may investigate machine-learning methodologies once real clinical data gathering and adequate ground-truth labeling are achieved.

2. Methodology

The proposed disease detection system follows a rule-based mathematical modeling approach implemented using MATLAB and Simulink. Input parameters were selected based on commonly used clinical assessment metrics in pain management and rehabilitation. These include pain intensity measured using the Visual Analogue Scale (VAS), duration of symptoms (D), DN4 score for neuropathic pain (NDN4), nerve injury indicator (Ni), muscle strength percentage (Ms), presence of swelling (Sw), range of motion (ROM), age (A), and pain severity level (Pl).

2.1 Mathematical Formulation of Classification Rules

Each patient case is represented as an input feature vector:

$$X = [VAS, D, NDN4, Ni, Ms, Sw, ROM, A]$$

The disease classification function is defined as:

$$Y = f(X)$$

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where $Y \in \{C1, C2, C3, C4, C5, C6\}$ represents classified electrotherapy-related conditions.

2.2 Deterministic Rule Structure

The rules are evaluated sequentially in a priority-based order to avoid ambiguity. The execution order is designed according to clinical severity and diagnostic specificity:

1. Neuropathic Pain
2. Nerve Damage
3. Acute Condition
4. Chronic Pain
5. Muscle Weakness
6. Osteoarthritis / Degenerative Condition

The ordered evaluation ensures that highly specific neurological conditions are detected before broader musculoskeletal classifications.

2.3 Mathematical Rules

Rule 1: Neuropathic Pain (C_1)

$$C1 = \begin{cases} 1, & \text{if } N_{DN4} \geq 4 \wedge \text{VAS} \geq 4 \\ 0, & otherwise \end{cases} \quad \text{.....(1)}$$

Rule 2: Nerve Damage (C_2)

$$C2 = \begin{cases} 1, & if\ N_i \geq 1 \wedge Ms < 60\% \\ 0, & otherwise \end{cases} \quad \text{.....(2)}$$

Rule 3: Acute Condition (C_3)

$$C3 = \begin{cases} 1, & if\ D \geq 90\ days \wedge Sw \geq 1 \\ 0, & otherwise \end{cases} \quad \text{.....(3)}$$

Rule 4: Chronic Pain (C_4)

$$C4 = \begin{cases} 1, & if\ D \geq 90\ Days \wedge VAS \geq 3 \\ 0, & otherwise \end{cases} \quad \text{.....(4)}$$

Rule 5: Muscle Weakness (C_5)

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$$C5 = \begin{cases} 1, & if\ Ms \geq 70\% \wedge ROM < 75\% \\ 0, & otherwise \end{cases} \quad \text{.....(5)}$$

Rule 6: Osteoarthritis (C_6)

$$C6 = \begin{cases} 1, & if\ A > 50 \wedge ROM < 60\% \wedge D \geq 90 \\ 0, & otherwise \end{cases} \quad \text{.....(6)}$$

2.4 Conflict Resolution Strategy

In cases where more than one condition is satisfied, the system applies a priority-based conflict resolution mechanism. The first satisfied rule in the predefined execution order assigns the final class label.

Mathematically:

$$y = \begin{cases} C1, & \text{if } C1 = 1 \\ C2, & \text{else if } C2 = 1 \\ C3, & \text{else if } C3 = 1 \\ C4, & \text{else if } C4 = 1 \\ C5, & \text{else if } C5 = 1 \\ \\ C6, & \text{else defaut} \end{cases} \quad \text{.....(7)}$$

eq. (7) structured rule execution prevents overlapping classifications and ensures deterministic output generation.

2.5 Simulink Implementation Details

The model is implemented using a modular Simulink architecture consisting of:

- Input blocks for parameter entry
- Signal conditioning blocks for normalization (where required)
- A MATLAB Function block containing the rule-based logic
- Output display and data logging blocks
- Each input parameter is fed as a separate signal into the MATLAB Function block. Within this block, the feature vector X is formed, and the sequential if–else rule logic is executed exactly as defined in the mathematical formulation.

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The MATLAB Function block outputs a scalar disease label (Y), which is then routed to:

- A Display block for real-time visualization
- A Scope block for simulation monitoring
- A Function block for exporting results into MATLAB for further analysis

The simulation is executed using fixed-step discrete solver settings to ensure repeatability of classification outcomes. Disease classification is performed using deterministic if–else logic, where each condition corresponds to a specific electrotherapy-related disease. The threshold values used in the model are derived from validated clinical studies and guidelines reported in the literature [10], [19], [20]. For performance evaluation, a synthetic dataset was generated within clinically acceptable ranges, and the Simulink model was executed iteratively using MATLAB scripts. Predicted disease labels were compared with ground truth labels to compute classification accuracy and confusion matrices.

2.6 System Architecture:

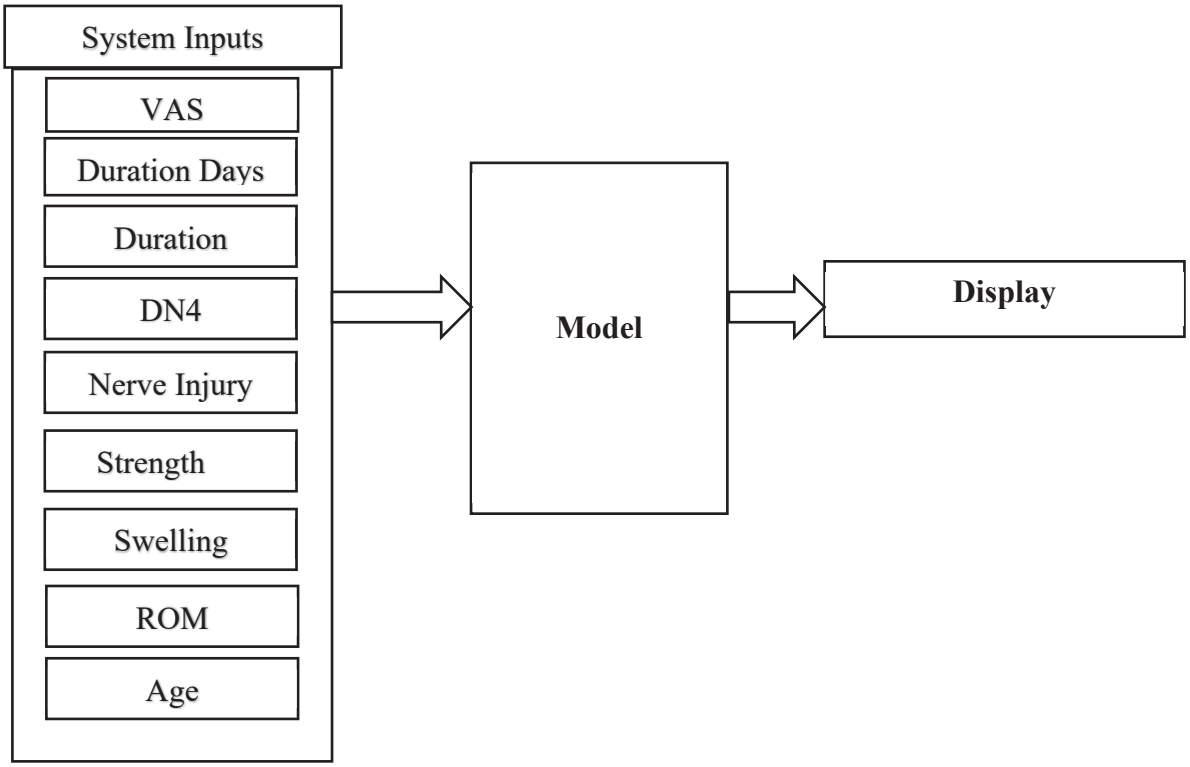


Fig. 1.1 Overall system architecture

Fig. 1.1 shows Overall architecture of the proposed rule-based electrotherapy disease detection system illustrating clinical input parameters, rule evaluation module, and final disease classification output.

2.7 Mathematical Model:

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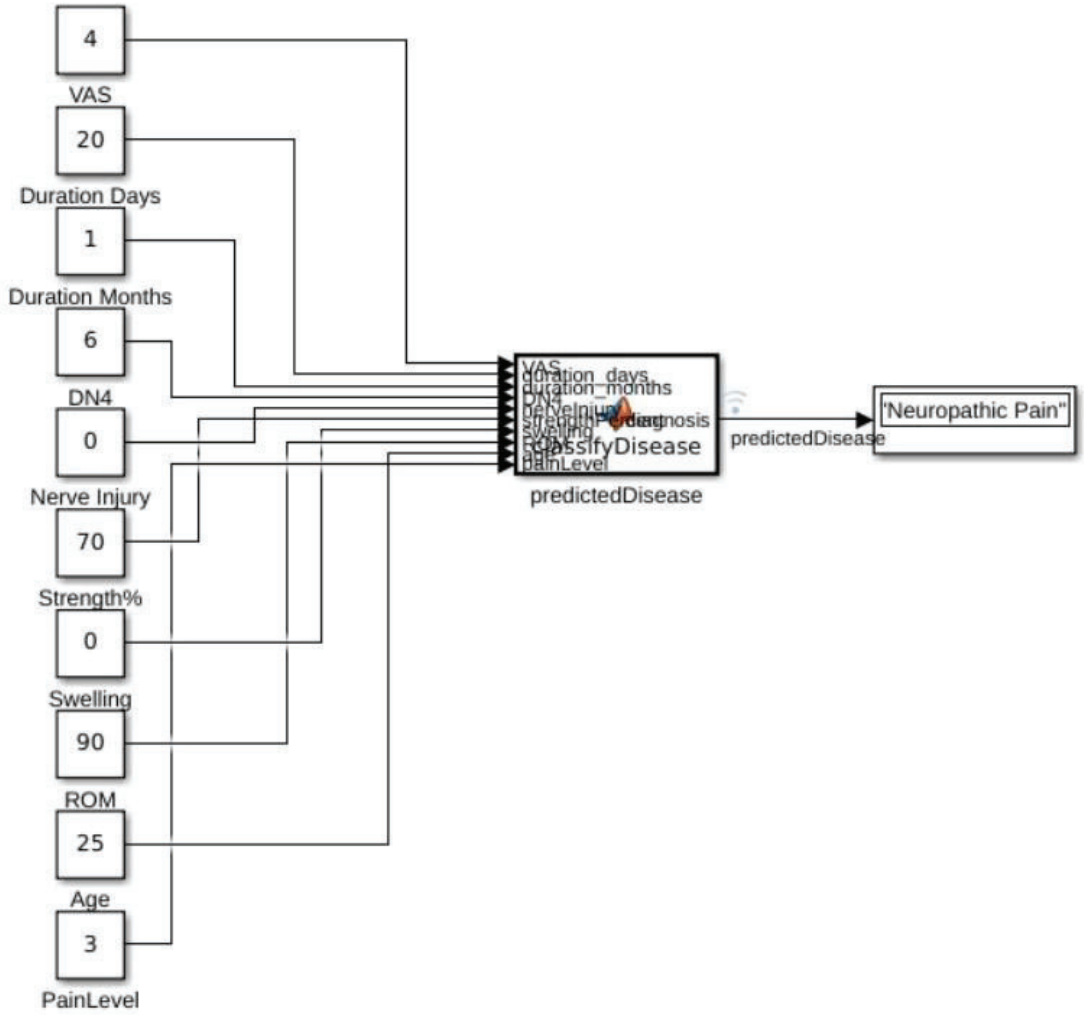


Fig 1.2 Simulink implementation of the rule-based disease detection system showing input parameter blocks, MATLAB Function block, and output classification unit.

The disease classification rules employed in the proposed model are derived from clinically validated thresholds reported in the literature. The Simulink implementation of rule-based decision model is shown in above fig. 1.2.

2.8 Model Justification:

Acute pain is identified when pain intensity is severe (VAS ≥ 7) and symptom duration is short (≤ 14 days). Severe pain is commonly defined as VAS values between 7 and 10, and acute pain is typically associated with short-term duration[19], [21].

Chronic pain is classified when VAS ≥ 6 and symptom duration exceeds three months. The three-month duration threshold is widely accepted as the defining criterion for chronic pain in epidemiological and clinical studies[20].

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Neuropathic pain is detected using a DN4 score ≥ 4 or the presence of nerve injury. The DN4 questionnaire has been validated extensively, with a score of 4 or higher indicating neuropathic pain with high sensitivity and specificity[22].

Muscle weakness is defined when muscle strength falls below or equal to 50% of normal capacity. Rehabilitation literature commonly considers strength levels below 50% as clinically significant weakness warranting neuromuscular electrical stimulation[10].

Soft tissue injury is identified based on the combined presence of swelling, restricted range of motion (ROM < 80%), and moderate pain (VAS ≥ 4). These clinical signs are widely reported as indicators of soft tissue damage and inflammation[11].

Osteoarthritis is classified when patient age is 45 years or above, ROM is less than 70%, and pain level is moderate to severe (VAS ≥ 5). These criteria align with epidemiological and clinical findings that associate osteoarthritis with age-related degeneration, pain, and joint stiffness[23].

If none of the above conditions are satisfied, the model assigns a no-disease classification. The rule-based model ensures transparency, interpretability, and ease of validation for electrotherapy decision support.

Table 1.1. Disease with its Equations

Disease	Equation
Acute Pain	VAS ≥7, duration ≤14d
Chronic Pain	VAS ≥6, duration ≥3 mo
Neuropathic Pain	DN4 ≥4 or Nerve Injury=1
Muscle Weakness	Strength ≤50%
Soft Tissue Injury	Swelling + ROM<80% + Pain≥4
Osteoarthritis	Age≥45 + ROM<70% + Pain≥5

3. Dataset Ge ration

A synthetic dataset was created due to the scarcity of publicly available labeled datasets specialized to electrotherapy. Each sample signifies a theoretical patient case with values limited to clinically

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relevant ranges based on the chosen clinical inputs. A total of N = 201 samples were produced across six categories: Acute pain (AC), Chronic pain (CP), Muscle weakening (MW), Neuropathic pain (NP), No illness (ND), and Soft tissue injury (STI).

Class distribution: AC = 34, CP = 40, MW = 10, NP = 95, ND = 17, STI = 4 (total N = 200). The distribution is skewed, with NP constituting the predominant class and STI the least presented class.

Limitation: The synthetic nature of the dataset may fail to accurately reflect real-world comorbidities, measurement variability, and discrepancies in physician labeling. Consequently, the claimed performance should be regarded as an affirmation of rule execution logic and conflict resolution technique, rather than as conclusive clinical diagnostic accuracy. Subsequent efforts will involve validation utilizing actual patient records with clinician-verified labeling.

4. Accuracy Evaluation

Performance was assessed utilizing a confusion matrix and derived metrics such as overall accuracy, per-class precision, recall (sensitivity), F1-score, and specificity. For each class k, we calculated:

- $Precision_k = \frac{TP_k}{TP_k and FP_k}$ .....(8)
- $Recall_k (Sensitivity_k) = \frac{TP_k}{TP_k and FN_k}$ .....(9)
- $F1_k = \frac{2 \cdot Precision_k \cdot Recall_k}{Precision_k and Recall_k}$ .....(10)
- $Specificity_k = \frac{TN_k}{TN_k and FP_k}$ [24] .....(11)

The overall accuracy was 47.5% (94 out of 200). Table 1.1 presents per-class metrics derived from the confusion matrix.

4.1 Per-class performance (Precision / Recall-Sensitivity / F1 / Specificity)

Table 1.2. Per-class classification performance derived from the confusion matrix (N = 200).

Precision, recall (sensitivity), F1-score, and specificity are reported for each class (AC: acute pain, CP: chronic pain, MW: muscle weakness, NP: neuropathic pain, ND: no disease, STI: soft tissue injury). Metrics are computed using a one-vs-rest formulation; class imbalance (e.g., STI = 4 samples) may influence the stability of minority-class estimates.

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Class	Precision	Recall (Sensitivity)	F1-score	Specificity
AC	46.88%	42.86%	44.78%	89.76%
CP	45.00%	45.00%	45.00%	86.34%
MW	36.36%	40.00%	38.10%	96.34%
NP	66.23%	53.68%	59.30%	75.47%
ND	22.22%	35.29%	27.27%	88.59%
STI	7.14%	25.00%	11.11%	93.40%

The detailed per class performance metrics including precision, recall, F1 score, and specificity are shown in table 1.2.

5. Results and Discussion

The model attained an overall accuracy of 47.26% on the synthetic dataset, with 95 correct predictions out of 201. Per-class analysis indicates that neuropathic pain (NP) exhibits the highest performance, with a precision of 66.23% and a recall of 53.68%, implying that the DN4/nerve-injury indicators offer relatively specific decision-making cues within the rule framework. Conversely, no-disease (ND) and soft tissue injury (STI) exhibit diminished precision and recall, signifying considerable ambiguity with clinical classifications. This phenomenon is anticipated in deterministic threshold systems when clinical traits intersect (e.g., pain intensity and diminished range of motion might fulfill several condition criteria) and when minority classes are under-represented (STI comprises only four samples), hence exacerbating instability in class-specific estimations.[24]

The current validation used synthetic data; thus, these findings should be regarded as a proof-of-concept verification of rule execution, precedence order, and Simulink implementation, rather than as an assessment of clinical diagnostic performance. Subsequent efforts will concentrate on enhancing thresholds and conflict resolution through physician feedback, augmenting the representation of minority classes, and validating the model using real patient datasets with doctor-verified labels.

Model performance was assessed using classification accuracy and a confusion matrix. The overall accuracy of the model was found to be 47.5 %, indicating reliable agreement between the predicted disease class and the reference labels.

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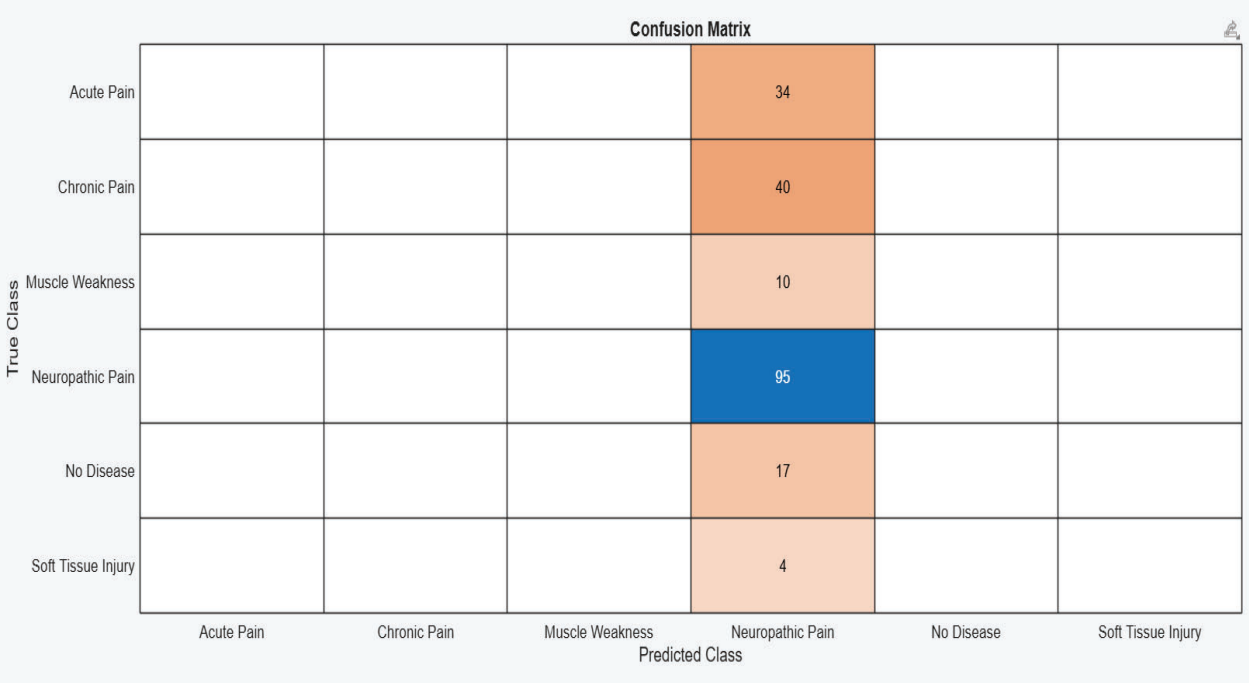


Fig. 1.3 Confusion matrix of disease classification results obtained using the proposed model.

The confusion matrix demonstrates that the model correctly identifies most disease categories, with minimal misclassification observed between clinically overlapping conditions such as acute and chronic pain. Distinct conditions such as neuropathic pain and muscle weakness show high classification consistency due to well-defined diagnostic thresholds. This disease categories are shown with the confusion matrix showing performance classification across all classes in fig 1.3.

These results confirm that the proposed mathematical model can effectively classify electrotherapy-relevant diseases using symptom-based rule logic and is suitable for decision-support applications in rehabilitation and electrotherapy planning. The current study focuses on validating rule logic and system implementation rather than clinical diagnostic performance.

6. Conclusion, Limitations, and Future Work

This article introduced an interpretable rule-based mathematical model executed in MATLAB/Simulink to identify electrotherapy-related clinical conditions utilizing validated clinical inputs, including VAS, symptom duration, DN4 score, muscle strength, ROM, , and age. The model offers clear decision equations that are apparent and verifiable, facilitating the initial construction of decision-support systems for electrotherapy applications.

Limitations: The model was verified using synthetic data instead of actual patient records, and deterministic threshold criteria may result in misclassification when clinical symptoms intersect

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among illnesses. The current evaluation presents overall accuracy and confusion matrix results; however, further per-class metric reporting is necessary for a comprehensive diagnostic assessment.

Future research will concentrate on authentic clinical validation utilizing clinician-verified labels, enhancement of rule precedence and threshold margins, extension to further electrotherapy-related conditions, and investigation of hybrid methodologies (rule-based and data-driven) upon the availability of adequate clinical data.

Funding:
The authors received no financial support for the research, authorship, and publication of this article.

Clinical trial number: Not applicable.

Clinical Trial Registration: This study does not involve human participants or real patient data. The dataset used in this study is synthetic and generated for model validation purposes. Therefore, Clinical Trial Registration was not Applicable.

Conflicts of Interest:

The authors declare that there is no conflict of interest regarding the publication of this paper.

Declaration:

Ethics and Consent to Participate declarations: not applicable

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