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IT3FLS-BASED ONTOLOGICAL FRAMEWORK FOR ASSESSING THE SUCCESS RATE OF PONSETI CASTING IN CLUBFOOT TREATMENT

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Abstract
Clubfoot represents a congenital deformity of the musculoskeletal system where the foot twists inward, often impairing gait and overall mobility if left uncorrected. Among available corrective methods, the Ponseti approach remains the gold standard for non-surgical treatment, employing systematic manipulation, sequential casting, and post-correction bracing to sustain alignment. In this study, a dataset comprising 3000 patient cases and 39 clinical, demographic, and functional features was analyzed to explore determinants influencing treatment success. Ontology-based data modeling was incorporated to enrich semantic understanding and ensure structured representation of clinical knowledge. The findings identified age at initial casting, affection type, and gender as primary factors shaping treatment response. Baseline functional scores (MFCS and HFCS) averaged between 2.25 and 2.5, indicating variations across individual cases. Principal Component Analysis underscored these variables as major contributors to outcome diversity. Employing the Interval Type-3 Fuzzy Logic System (IT3FLS) yielded accurate predictive results (RMSE = 0.3414; MSE = 0.1165; MAE = 0.3066; MAPE = 30.66%), confirming its robustness for clinical analytics and outcome evaluation in Ponseti casting.

Keywords: Ponseti casting, clubfoot, IT3FL, PCA, Evaluation Metrics

Introduction
One of the most common congenital deformities in newborns is clubfoot, which can be effectively managed using the Ponseti method, a non-surgical approach based on a detailed understanding of the condition's pathoanatomy (Vaishy *et al.,* 2020). Medically known as congenital talipes equinovarus, it affects about 1.2 per 1,000 live births worldwide (Aroojis et al., 2021). The condition involves an inward and downward twisting of the foot, which can significantly limit mobility if untreated. The Ponseti Method, pioneered by Dr. Ignacio Ponseti, offers a non-surgical solution through weekly manipulations and serial casting over five to eight weeks, followed by extended bracing to prevent recurrence (Malhotra et al., 2018; Walter et al., 2020). Clubfoot manifests mainly in two forms: idiopathic (80%), which arises from genetic, environmental, vascular, and positional factors, and secondary (20%), often associated with syndromes such as Moebius or neurofibromatosis (Ganesan et al., 2021). More complex or atypical cases feature shorter, rigid feet with pronounced midfoot curvature (Dibello et al., 2020). Early

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detection, frequently via prenatal ultrasound between 18–24 weeks, is critical to successful intervention (Gupta et al., 2023). The effectiveness of Ponseti casting is influenced by factors including the severity at presentation, patient age, genetic predispositions, and precise cast application (Mohan et al., 2023). Ontologies allow for easy and intelligent reasoning with knowledge and is therefore the answer to technology issues, knowledge management as a whole, and the big dream of artificial intelligence Usip and Ntekop 2016). The Conventional prediction methods rely on clinical judgment, which may not fully capture the multifactorial dynamics of the condition. Advanced predictive approaches utilizing machine learning (ML), neural networks, and fuzzy logic provide a more nuanced, data-driven perspective. Hybrid models combine these techniques: ML uncovers hidden patterns in large datasets, neural networks model complex relationships (Punia et al., 2021), and fuzzy logic addresses uncertainty in medical data (Ali, 2023). Fuzzy logic, introduced by Lotfi Zadeh in 1965, enables reasoning with degrees of truth rather than binary outcomes, allowing elements to partially belong to multiple categories (Ganaie et al., 2023; Umoh et al., 2019). Interval Type-3 Fuzzy Logic (IT3FL) further extends this framework, accommodating higher-order uncertainty in complex medical decision-making (Castillo et al., 2014; Umoh et al., 2017).

High-quality patient data including demographics, clinical measures, imaging, and treatment outcomes is fundamental for predictive modeling (Bhatt et al., 2023). Preprocessing steps such as normalization, handling missing values, and encoding categorical variables ensure the dataset is suitable for analysis (Bozhenko and Tatarnikova., 2023). By integrating IT3FL and voting ensemble methods, the hybrid framework improves predictive reliability, providing actionable insights for Ponseti casting outcomes and supporting personalized strategies for effective clubfoot correction.

Clinical outcomes and factors influencing success of the Ponseti method

The Ponseti method (serial manipulation, casting and bracing, with selective tenotomy) is the global gold standard for initial conservative management of idiopathic clubfoot, with large multi-center reviews and longitudinal series reporting overall success rates commonly above 90% when protocol and bracing adherence are maintained. Evidence across settings shows variation in reported success (range in some reviews from ≈55% up to near 100%), with relapse strongly associated with poor brace adherence, late presentation, and variations in casting technique or follow-up. Several recent single-center outcome studies (including 5-year follow-ups) confirm high short-term correction rates but highlight relapse and functional outcome heterogeneity tied to socio-demographic and care-delivery factors. These clinical findings establish the core measurement targets and the relevant input features for any computational assessment of casting success: initial severity scores, age at first cast, unilateral vs bilateral involvement, number of casts, need for tenotomy, bracing adherence, and follow-up (Maghfuri et al., 2024). Existing outcome work therefore provides both (a) the target variables that an assessment framework must predict/monitor, and (b) examples of sources of uncertainty (measurement variability, incomplete adherence data, and heterogeneous follow-up) that motivate advanced uncertainty-aware modeling (Bitew et al., 2022).

Fuzzy logic for medical decision support and uncertainty handling

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Fuzzy logic methods Type-1, Type-2 and, more recently, Interval Type-3 (IT3) fuzzy logic systems have been explored for medical classification and decision support because they can represent vagueness and linguistic uncertainty in clinician knowledge and noisy measurements. Interval Type-3 FLSs extend the uncertainty envelope beyond Type-2 by providing an extra layer for modelling higher-order uncertainty (useful where expert rules, sensor noise, and inter-rater variability coexist). Recent work has demonstrated IT3FIS/IT3FLS designs for medical classification problems and control tasks, and shown that evolutionary optimization (e.g., genetic algorithms) can tune membership parameters and rule bases to improve classification robustness (Melin et al., 2023). For the Ponseti success problem the key advantages of IT3FLS are (1) graceful handling of imprecise clinical inputs (e.g., "moderate" stiffness, "poor" brace adherence reported by caregivers), (2) capacity to combine expert rules with data-driven tuning, and (3) improved robustness to noisy/limited datasets compared with lower-order fuzzy models — all properties shown in recent comparative studies and bibliometric reviews of Type-3 FLS applications. These properties make IT3FLS a promising inference engine when the goal is to predict/categorize likely casting outcomes under real-world uncertainties (Valdez et al., 2025)

Ontologies and hybrid ontology–fuzzy frameworks in clinical decision support

Ontologies have a long track record in clinical decision support for structuring domain knowledge, enabling semantic interoperability, and codifying guideline rules; ontological CDSS implementations (and standards such as SNOMED CT) are used to represent clinical concepts, relationships and to drive rule engines (Jing et al., 2023). In orthopaedics and pediatric musculoskeletal assessment, researchers have developed domain ontologies and prototype computer-aided decision systems that formalize diagnostic and severity concepts for lower-limb deformities (including clubfoot), demonstrating that ontological knowledge bases can improve consistency of clinical characterization and support automated reasoning (Dao et al., 2011). Hybrid approaches that combine ontologies (for crisp semantic representation and data integration) with fuzzy inference (for uncertainty-tolerant reasoning) are increasingly proposed in the literature for complex clinical problems. Ontologies provide a controlled vocabulary and relations (patient, measurement, protocol, outcome), while IT3FLS provides the uncertainty-robust inference needed to map heterogeneous inputs to probabilistic or linguistic outcome classes. Examples from medication safety CDSS and other clinical applications show ontology-backed rule management and explainable alerts; similar architectural patterns can be adapted to Ponseti casting assessment to deliver transparent, semantically grounded, and uncertainty-aware decision support (Calvo-Cidoncha et al., 2022).

Methodology

This study utilized a hybrid computational intelligence framework combining voting ensemble learning models with an IT3FLS (Interval Type-3 Fuzzy Logic System) approach. The system architecture, depicted in Figure 1, outlines the complete workflow and consists of several key components: Ponseti casting factors, a data preprocessing module, a structured database, an ensemble learning engine, an IT3FLS inference engine, output generation, and evaluation mechanisms. This comprehensive design establishes a seamless pipeline for analyzing, predicting, and assessing the success of Ponseti casting in the treatment of clubfoot.

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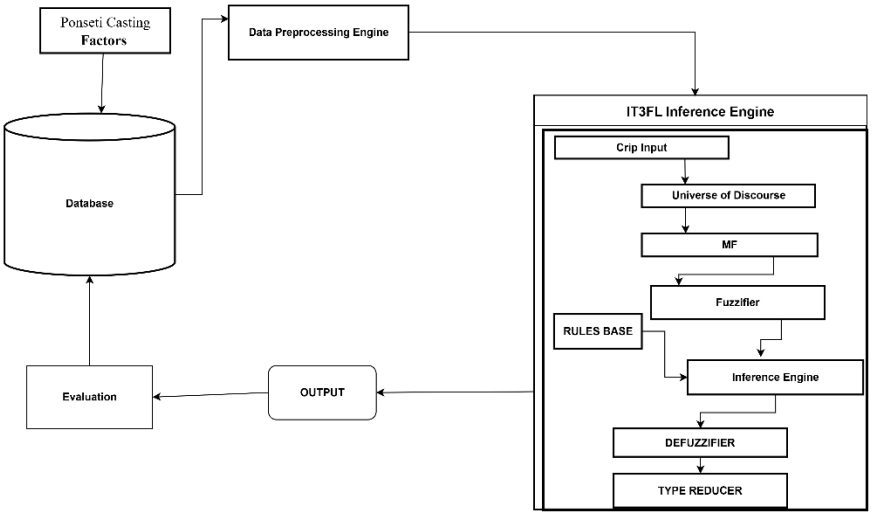

Figure 1: Architecture of Hybrid Intelligent Models for Assessing Ponseti Casting Success Rate During Clubfoot Treatment

Experimentation and Analysis

Conceptual Ontology for Measuring the Effectiveness of Ponseti Casting in Managing Clubfoot

The constructed ontology systematically organizes all critical aspects of Ponseti casting into a structured, patient-oriented framework. At its center lies the Patient class, which contains essential information such as gender, age at first casting, and affection type. Linked subclasses, including BaselineAssessment, record key initial parameters HFCS, MFCS, and TotalScore for both feet. Additional components, such as BraceCompliance, CastingAfterRelapse, and DurationOnBrace_Weeks, monitor adherence, relapse management, and brace usage period, providing a comprehensive representation of each child's treatment journey. In this study, Figure 2 acts as a digital backbone connecting patient data, treatment parameters, and clinical outcomes. Through the semantic integration of medical and behavioral attributes, the ontology facilitates intelligent reasoning using an Interval Type-3 Fuzzy Logic System (IT3FLS). This system interprets the uncertainty inherent in-patient conditions and treatment responses, allowing for nuanced assessment of casting outcomes. By leveraging the structured ontology, the IT3FLS evaluates the likelihood of treatment success or relapse in a manner that is both data-driven and patient-centered, capturing the human variability embedded within real clinical experiences.

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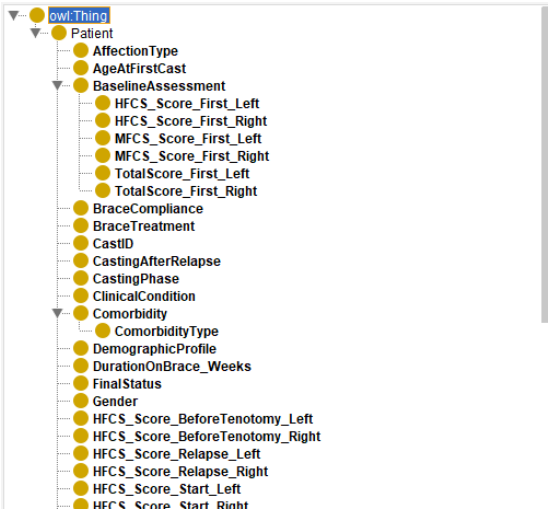

Figure 2: Hierarchical Organization of Annotation Property Classes within the Clubfoot Ontology

Figure 2 illustrates has Outcome as the pivotal relationship linking every stage of the Ponseti casting procedure to its therapeutic outcomes. Its sub-properties experienced Brace Treatment, underwent Casting Phase, and has Demographic Profile represent key components such as post-casting brace management, corrective phase progression, and essential demographic attributes including age and gender. Clearly defined domains and ranges establish how these relationships function: some correspond to physical outcomes like transverse or symmetrical alignment, while others provide self-referential indicators useful for tracking patient improvement. The emphasized Outcome node serves as the structural anchor, integrating all patient-related information into a unified framework that supports the evaluation of treatment effectiveness.

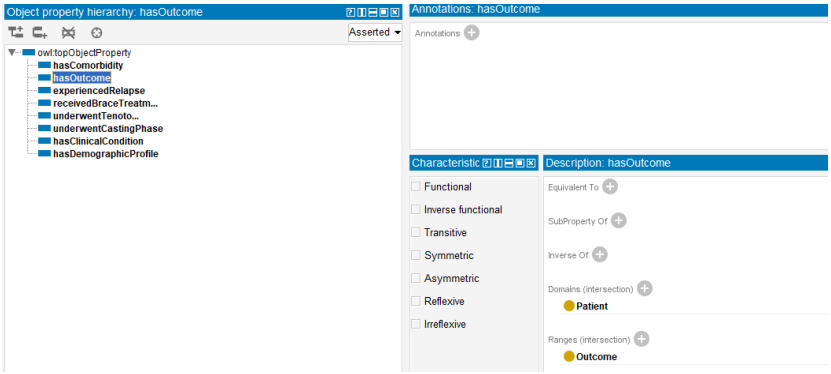

Figure 3: Object Property Hierarchy Illustrating Connections Between Clinical Data and Demographics in Ponseti Casting Evaluation

Figure 3 presents the structured data properties in a circular layout, providing an intuitive overview of the measurable indicators that track progress in Ponseti treatment. On the left, the owl:top Data

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Property section enumerates critical metrics such as has MFCS_Relapse_Right (foot function score following relapse), has Duration On Brace Weeks (duration of brace use for maintaining correction), and has Age At First Cast (the patient's age at the initiation of treatment, an important determinant of success). Extending outward from the central Patient node, highlighted yellow branches depict outcome-related measures including Total Score Start, Relapse Status, Tenotomy Procedure, and Casting Phase, demonstrating how patient demographics and clinical data are interconnected to produce a comprehensive view of the treatment journey.

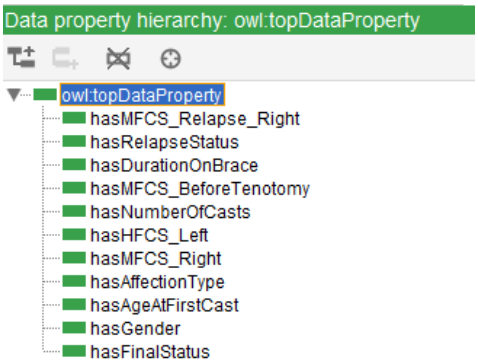

Figure 4: Data Property Network for Predicting Ponseti Casting Success

Figure 4 provides a visual representation of how a child's Ponseti clubfoot treatment information is structured and interlinked. At the core lies the Patient node, which connects to essential details influencing outcomes, including demographic data like Gender and TenotomyProcedure, clinical measurements such as HFCS_Score_Relapse_Left and TotalScore_Start, and key outcome indicators highlighted in yellow nodes, including Outcome, RelapseStatus, and FinalStatus. Additional branches depict treatment progression (CastingPhase, BraceCompliance) and contextual factors (DemographicProfile, Comorbidity), offering a clear and integrated overview of each patient's treatment pathway and predicted outcomes.

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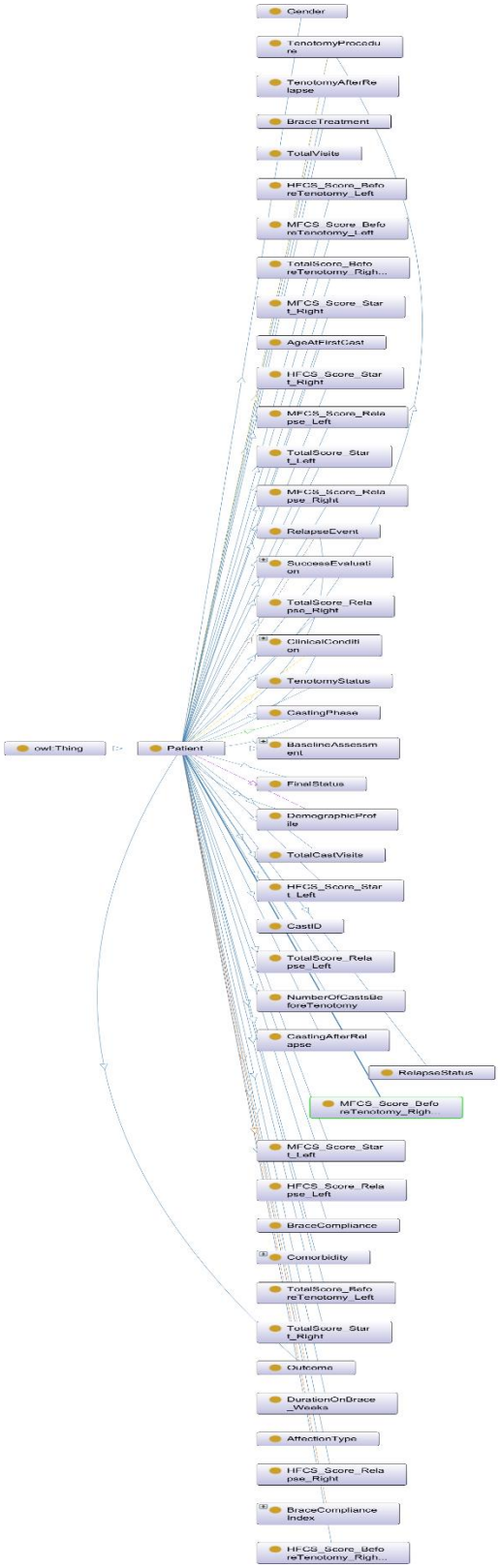

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Figure 5: Comprehensive Ontology Network for Ponseti Treatment Success Prediction

SWRL Rule For the Success Rate of Ponseti Casting in The Treatment of Clubfoot

Moderate Outcome Rule

Patient(?p) ^ TenotomyProcedure(?t) ^ underwentTenotomy(?p, ?t) ^ TenotomyStatus(?t, "Yes") ^ BraceTreatment(?b) ^ receivedBraceTreatment(?p, ?b) ^ BraceCompliance(?b, "Moderate") ^ RelapseEvent(?r) ^ experiencedRelapse(?p, ?r) ^ RelapseStatus(?r, "No") ^ Outcome(?o) ^ hasOutcome(?p, ?o)→ PartiallySuccessfulTreatment(?o).

Relapse After Treatment Rule

Patient(?p) ^ BraceTreatment(?b) ^ receivedBraceTreatment(?p, ?b) ^ RelapseEvent(?r) ^

experiencedRelapse(?p, ?r) ^ RelapseStatus(?r, "Yes") ^ CastingAfterRelapse(?b, "Yes") → UndergoingSecondaryTreatment(?p)

Descriptive Statistics

Table 1 presents the descriptive statistics for the dataset used to assess the success of Ponseti casting in clubfoot treatment. The dataset, Ponseti_casting.csv, comprises 3000 records across 39 features. Of these, 24 features are categorical, including attributes such as gender, clubfoot type, and treatment protocol, while 6 features are numeric, covering measures like age at first cast and other clinical parameters. This composition emphasizes the dominance of categorical data, supplemented by essential quantitative variables, providing a robust foundation for both statistical analysis and predictive modeling.

Table 4: Description Statistics for the success rate of Ponseti casting in the treatment of clubfoot

Dataset Name	Dataset Size		Features	
	Rows	Columns	Categorical	Numeric
Ponseti casting.csv	3000	39	10	29

Line Plots for numerical columns on Ponseti casting in the treatment of clubfoot

MFCS values at the first presentation for the right foot show considerable variation across the first 50 samples, with scores ranging from 1.8 to 3.0, as shown in Figure 6. Early samples (0–20) fluctuate between roughly 2.0 and 2.8, with noticeable peaks near samples 5, 15, and 25. From sample 20 onward, scores stabilize around 2.6, indicating a dynamic initial range before settling into a more consistent value.

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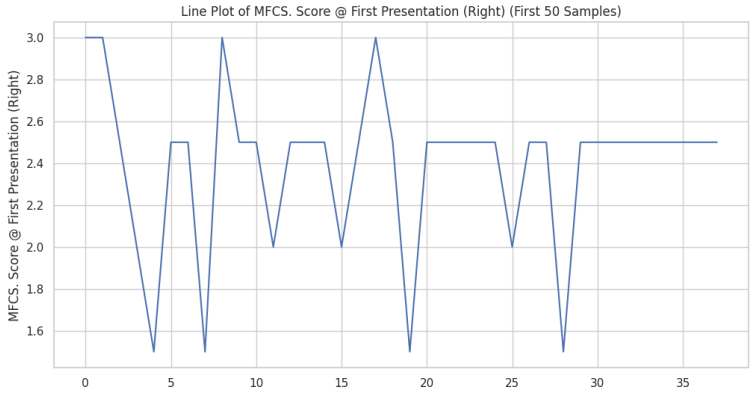

Figure 6: Line plot for MFCS Score @ First Presentation (Right)

HFCS scores at the initial presentation for the right foot vary across the first 50 samples, ranging from 1.0 to 3.0, as illustrated in Figure 7. Early samples (0–20) fluctuate between roughly 2.0 and 2.75, with peaks near samples 5, 10, and 15. After sample 20, scores generally stabilize around 2.5, except for a brief drop to about 1.5 near sample 25 before returning to 2.5, reflecting initial variability followed by a more consistent pattern.

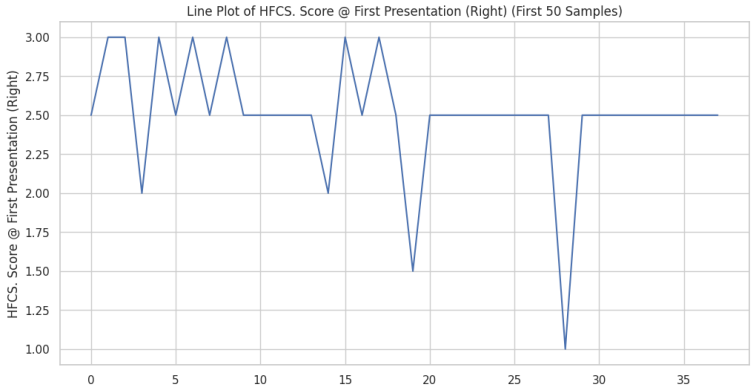

Figure 7: Line plot for HFCS Score @ First Presentation (Right)

Total scores at the initial presentation for the right foot show considerable variation across the first 50 samples, ranging from 2.5 to 6.0, as shown in Figure 8. Early samples (0–20) fluctuate between roughly 4.0 and 5.5, with notable peaks near samples 5 and 15. After sample 20, scores stabilize around 5.0, except for a sharp dip to about 3.0 near sample 25 before returning to 5.0, illustrating an initially dynamic range that later settles into a more consistent trend.

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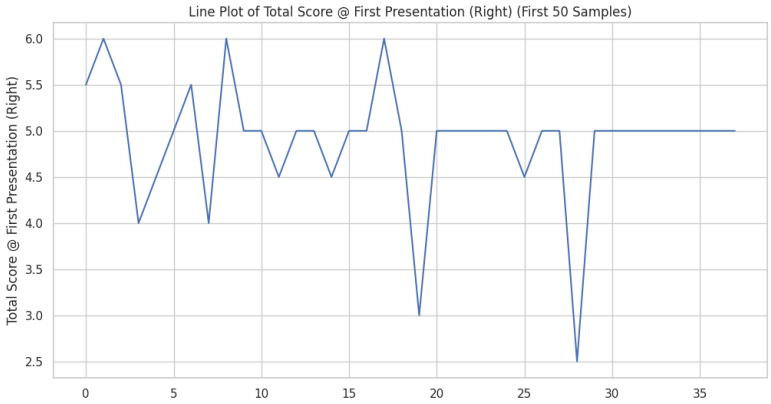

Figure 8: Line plot for Total Score @ First Presentation (Right)

Correlation of Attribute

The feature correlation heatmap, presented in Figure 9, illustrates the relationships between various medical attributes and scores. Using a color gradient from blue (negative correlations) to red (positive correlations), the heatmap shows correlation strength on a scale from -1.0 to 1.0. Attributes include age, gender, affection type (unilateral/bilateral), and scores such as MFCS and Total Score measured at different stages initial presentation, pre- and post-tenotomy, and relapse diagnosis. Dark red areas highlight strong positive correlations, for example, between MFCS Score @ First Presentation (Right) and Total Score @ First Presentation (Left), while blue regions indicate negative correlations. Overall, the heatmap reveals patterns and interdependencies among variables, aiding medical analysis and treatment planning.

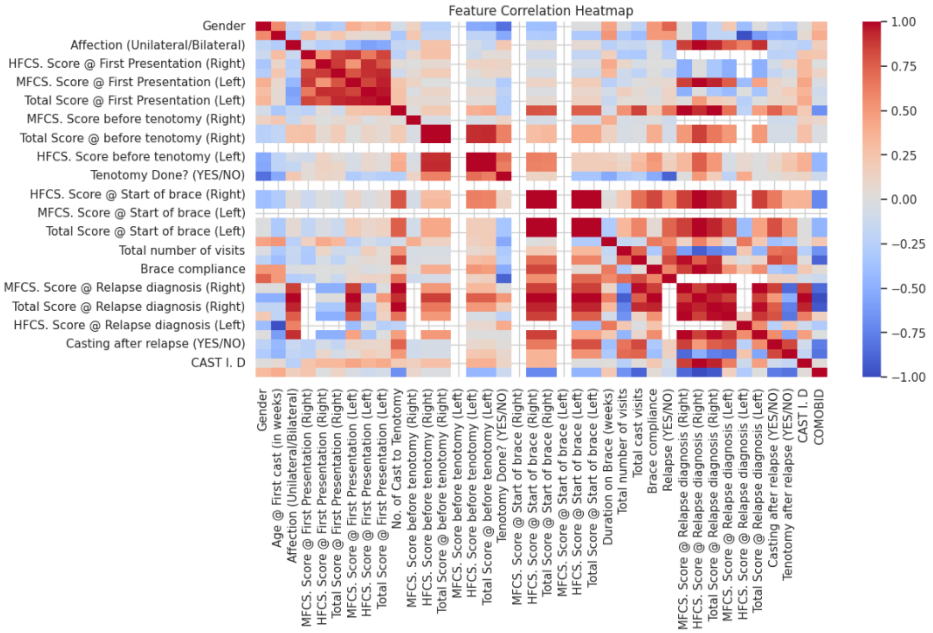

Figure 9: Correlation of Attribute

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Data Preprocessing

Table 3 summarizes the results of the Principal Component Analysis (PCA) conducted on the dataset attributes. Each feature is associated with a principal component (PC), along with its corresponding eigenvalue and the proportion of variance it explains. PC1 (Gender) exhibits the highest eigenvalue of 5.5391, accounting for 15.41% of the total variance. This is followed by PC2 (Age at First Cast) and PC3 (Affection), with eigenvalues of 4.6470 and 4.5770, representing 12.93% and 12.73% of variance, respectively. Later components, including MFCS and HFCS scores for both feet (PC4–PC8) and the Total Score at first presentation (PC6), show smaller eigenvalues ranging from 1.0903 to 2.0430, explaining between 3.03% and 5.68% of the variance. Overall, gender, age, and affection are the dominant contributors to variability, whereas the clinical score measures provide smaller but meaningful contributions.

Table 3: PCA Attribute Values

S/N	Attribute	Component	Eigenvalue	Variance Explained
1	Gender	PC1	5.5391	0.1541
2	Age @ First cast (in weeks)	PC2	4.6470	0.1293
3	Affection (Unilateral/Bilateral)	PC3	4.5770	0.1273
4	MFCS. Score @ First Presentation (Right)	PC4	2.0430	0.0568
5	HFCS. Score @ First Presentation (Right)	PC5	1.7809	0.0495
6	Total Score @ First Presentation (Right):	PC6	1.6976	0.0472
7	MFCS. Score @ First Presentation (Left)	PC7	1.2379	0.0344
8	HFCS. Score @ First Presentation (Left)	PC8	1.0903	0.0303

Figure 10 displays the eigenvalues corresponding to each principal component (PC1–PC8). The x-axis represents the principal components, and the y-axis shows their respective eigenvalues, which indicate the proportion of variance explained. A sharp decline is observed from approximately 9 for the first component to around 2 by the fourth component, followed by a flattening near 1, forming a distinct ‘elbow’ pattern. This pattern suggests that the first four components account for the majority of variance in the dataset, while the subsequent components contribute progressively less to the overall variability.

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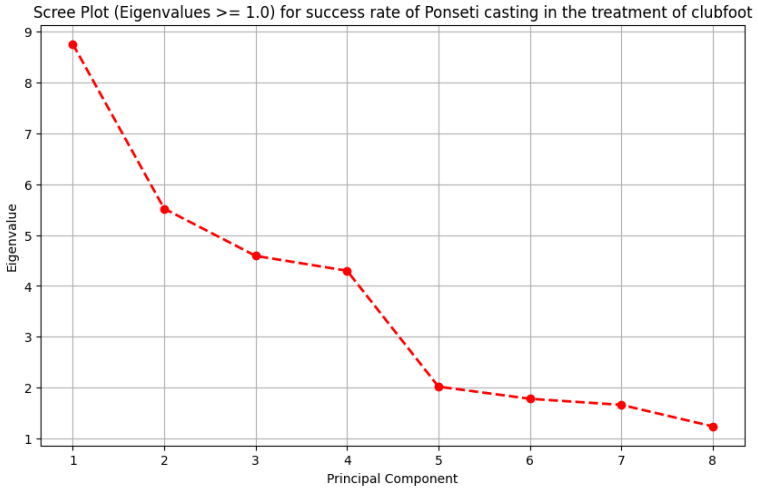

Figure 10: Scree Plot representation for PCA Values

IT3FL Model Building

Membership Function for IT3FL

The membership function plot for Gender, shown in Figure 11, presents a membership function (MF) plot titled "Input 1: Gender," which depicts the degree of membership for three gender categories, Female, and Male, across a range of Gender MF values from 0 to 4. The y-axis represents membership values from 0 to 1, indicating the strength of association with each category, while the x-axis corresponds to the Gender MF input variable.

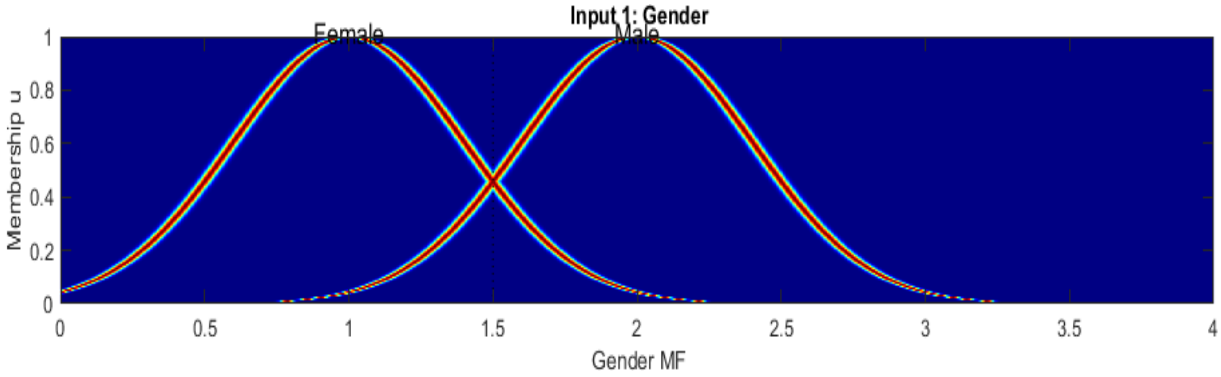

Figure 11: Input MF for Gender

The membership function plot for AgeWeeks, shown in Figure 12, represents the degree to which values belong to three categories: Newborn, Juvenile, and Adult. The x-axis spans AgeWeeks from 0 to 4, and the y-axis shows membership degrees from 0 to 1. The plot features overlapping bell-shaped curves: Newborn peaks at 1 near 0.5, Juvenile peaks around 2, and Adult peaks near 3.5.

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These overlaps reflect the IT3FL approach, allowing values to partially belong to multiple categories, enabling smooth transitions and capturing gradual variations in age.

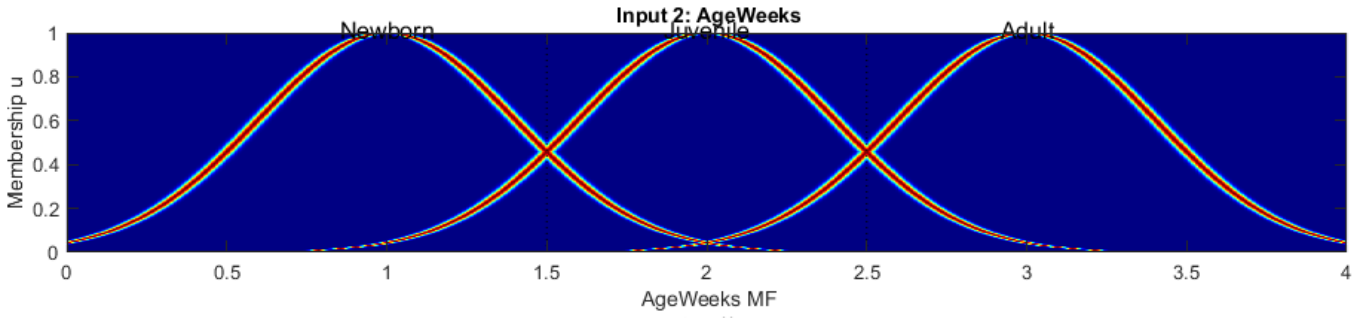

Figure 12: Input MF for Ageweeks

Figure 13 presents a membership function (MF) plot titled "Input 3: Affection," depicting the degree of membership for three affection levels Low, Medium, and High across Affection MF values from 0 to 4. The x-axis represents the Affection input variable, while the y-axis shows membership values from 0 to 1, indicating how strongly each value aligns with a given category. The plot displays three overlapping bell-shaped curves: Low peaks at 1 around 0.5, Medium reaches its maximum near 2, and High peaks around 3.5. The overlapping regions reflect IT3FL, allowing intermediate affection values to partially belong to multiple categories, ensuring smooth transitions and accommodating gradual variations in affection levels.

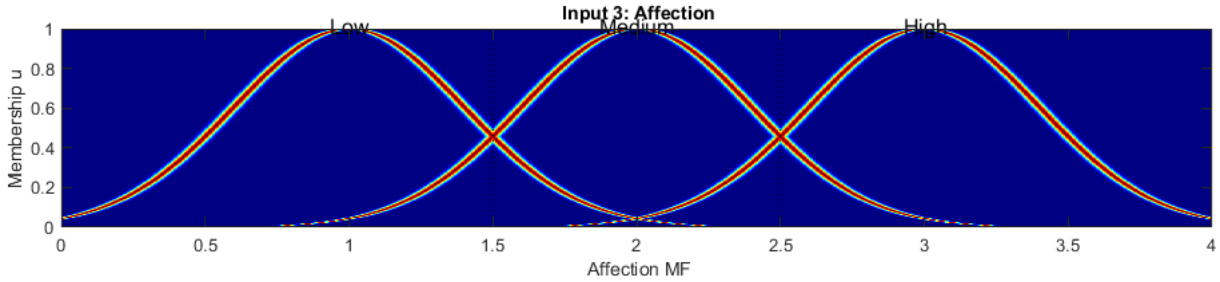

Figure 13: Input MF for Affection

The membership function plot for relapse severity, shown in Figure 14, illustrates the degree of membership for three levels: Low, Medium, and High, across Relapse MF values from 0 to 4. The x-axis represents the relapse variable, while the y-axis shows membership values from 0 to 1. The plot displays overlapping bell-shaped curves: Low peaks at 1 near 0.5, Medium peaks around 2, and High peaks near 3.5. These overlaps reflect the IT3FL approach, allowing intermediate values to belong partially to multiple categories, enabling smooth transitions between relapse severity levels.

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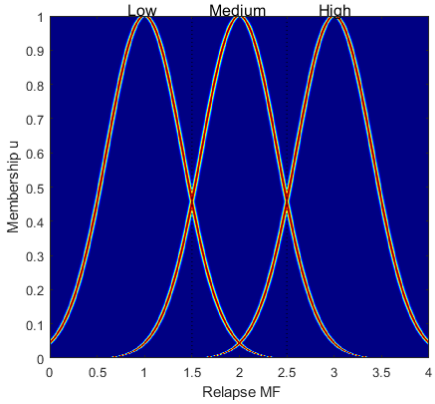

Figure 14: Output MF for Relapse

Rules for IT3FL

Rule 1: IF Gender is Female AND AgeWeeks is Newborn AND Affection is Low THEN Low

Rule 2: IF Gender is Male AND AgeWeeks is Newborn AND Affection is Low THEN Low

Rule 3: IF AND AgeWeeks is Newborn AND Affection is Low THEN Medium

Rule 4: IF Gender is Female AND AgeWeeks is Juvenile AND Affection is Low THEN Low

Rule 5: IF Gender is Male AND AgeWeeks is Juvenile AND Affection is Low THEN Medium

Rule 6: IF AND AgeWeeks is Juvenile AND Affection is Low THEN Medium

Rule 7: IF Gender is Female AND AgeWeeks is Adult AND Affection is Low THEN Medium

Rule 8: IF Gender is Male AND AgeWeeks is Adult AND Affection is Low THEN Medium

Rule 9: IF Gender is Female AND AgeWeeks is Adult AND Affection is Low THEN Medium

Rule 10: IF Gender is Female AND AgeWeeks is Newborn AND Affection is Medium THEN Low

Evaluation plots against Epoch

Figure 15 presents three plots illustrating the performance of a model over successive training epochs using key evaluation metrics: RMSE, MAE, and MAPE. The top plot, "RMSE vs. Epoch," depicts the Root Mean Square Error (RMSE) in blue, which begins around 0.7 and steadily declines to approximately 0.1, indicating a substantial improvement in predictive accuracy as training progresses. The middle plot, "MAE vs. Epoch," shows the Mean Absolute Error (MAE) in green, starting near 0.6 and reducing to about 0.1, reflecting a consistent decrease in absolute error and reinforcing the model's increasing reliability. The bottom plot, "MAPE vs. Epoch," illustrates the Mean Absolute Percentage Error (MAPE) in red, beginning at approximately 70% and dropping to around 10%, highlighting a marked reduction in relative prediction error. Together, these plots demonstrate that the model not only learns effectively over time but also achieves stable and accurate predictions, indicating robust convergence and strong overall performance.

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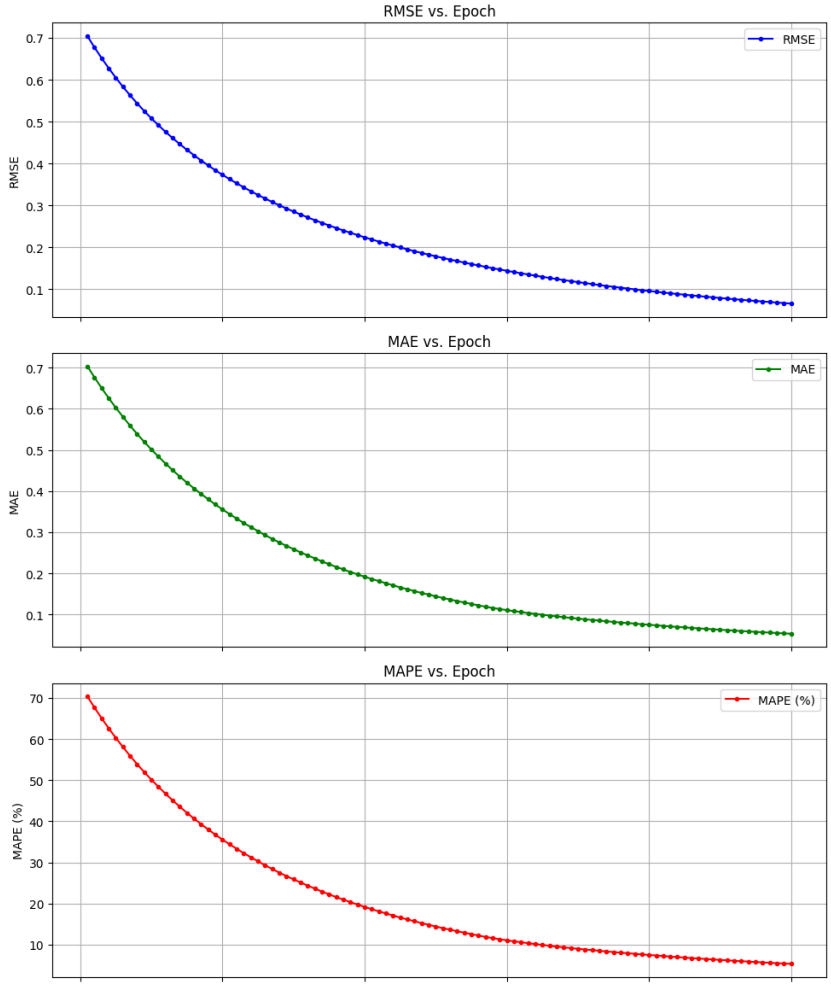

Figure 15: Plot of Evaluation Metrics

Table 4 summarizes the optimal performance metrics obtained during the training epoch. The Root Mean Square Error (RMSE) is 0.3414, while the Mean Squared Error (MSE) is 0.1165, indicating the overall prediction errors of the model. The Mean Absolute Error (MAE) is 0.3066, reflecting the average magnitude of the errors without considering their direction. The Mean Absolute Percentage Error (MAPE) is 30.66%, representing the average prediction error as a percentage of the actual values. Together, these metrics provide a comprehensive assessment of the model's accuracy and predictive performance.

Table 4: IT3FL Performance Metrics Obtained During the Epoch

Performance Metric	**Value**
RMSE	0.3414
MSE	0.1165

MAE	0.3066
MAPE	30.66%

Conclusion

The results of this study indicate that Ponseti casting continues to be an effective non-surgical method for correcting clubfoot, with treatment outcomes influenced by patient-specific variables such as age at first cast, type of affection, and gender. Statistical evaluation showed that functional scores, including MFCS and HFCS, generally cluster around 2.25–2.5, while variation in clinical parameters highlights the importance of accounting for individual differences when planning treatment. Principal Component Analysis identified Gender, Age at First Cast, and Affection as the primary contributors to variability, shedding light on the factors that most strongly affect treatment outcomes. Demonstrated performance (RMSE = 0.3414; MSE = 0.1165; MAE = 0.3066; MAPE = 30.66%) confirms its effectiveness for clinical decision support. Overall, the findings reinforce the value of data-driven decision-making in Ponseti casting, emphasizing early intervention and personalized treatment strategies to optimize functional correction and minimize relapse in children with clubfoot.

Recommendations

Based on the findings of this study, the following recommendations were made:

1. Medical and health education practitioners should sensitise the populace that improved early diagnosis, prompt referral systems, and increased parental awareness are essential.
2. Patient-specific treatment planning is encouraged, given that factors such as affection type and gender significantly influence outcomes, indicating the need for personalized clinical decision-making rather than generalized treatment protocols.
3. The integration of ontology-driven decision-support systems into orthopedic practice is encouraged to enhance data consistency, interpretability, and evidence-based decision-making, as demonstrated by the improved predictive reliability of the ontology-enhanced ensemble model.
4. The adoption of machine learning ensemble approaches in clinical analytics is recommended, since the Voting Ensemble Classifier achieved a predictive accuracy of 80%, highlighting its robustness and suitability for outcome prediction.
5. Healthcare policymakers and administrators should support the deployment of intelligent clinical decision-support systems through investments in data infrastructure, interdisciplinary collaboration, and clinician training to enhance pediatric orthopedic care.

References

Ali, M. (2023). The Hybrid Neuro-Fuzzy Models' Most General Intelligent Architectures. https://doi.org/10.31219/osf.io/zab6k

Bhatt, A. (2023). Data quality – The foundation of real-world studies. Perspectives in Clinical Research, 14(2), 92. https://doi.org/10.4103/picr.picr_12_23

Bitew, A., Melesse, D. Y., & Admass, B. A. (2023). A 5-years results of the Ponseti method in the treatment of congenital clubfoot: a retrospective study. European Journal of Orthopaedic Surgery & Traumatology, 33(5), 1781-1787.

Bozhenko, V. V., & Tatarnikova, T. M. (2023). Application of Data Preprocessing in Medical Research. https://doi.org/10.1109/weconf57201.2023.10148004

Calvo-Cidoncha, E., Camacho-Hernando, C., Feu, F., Pastor-Duran, X., Codina-Jané, C., & Lozano-Rubí, R. (2022). OntoPharma: ontology based clinical decision support system to reduce medication prescribing errors. BMC Medical Informatics and Decision Making, 22(1), 238.

Castillo, O., & Melin, P. (2014). A review on interval type-2 fuzzy logic applications in intelligent control. Information Sciences, 279, 615-631. https://doi.org/10.1016/j.ins.2014.04.015

Chopra, H., Annu, N., Shin, D. K., Munjal, K., Priyanka, N., Dhama, K., & Emran, T. B. (2023). Revolutionizing clinical trials: the role of AI in accelerating medical breakthroughs. International Journal of Surgery, 109(12), 4211–4220. https://doi.org/10.1097/js9.0000000000000705

Dao, T. T., Marin, F., Bensahel, H., & Tho, M. C. H. B. (2011). Computer-Aided decision system for the clubfeet deformities. Advances in Experimental Medicine and Biology, 623–635. https://doi.org/10.1007/978-1-4419-7046-6_64

Dibello, D., Di Carlo, V., Colin, G., Barbi, E., & Galimberti, A. M. C. (2020). What a paediatrician should know about congenital clubfoot. the Italian Journal of Pediatrics/Italian Journal of Pediatrics, 46(1). https://doi.org/10.1186/s13052-020-00842-3

Ganaie, F. R. (2023b). Application of Fuzzy Logic in Artificial Intelligence. International Journal for Research in Applied Science and Engineering Technology, 11(4), 2350–2356. https://doi.org/10.22214/ijraset.2023.50672

Ganesan, B., Yip, J., Luximon, A., Gibbons, P. J., Chivers, A., Balasankar, S. K., & Al-Jumaily, A. (2021). Infrared Thermal Imaging for Evaluation of Clubfoot After the Ponseti Casting Method—An Exploratory Study. Frontiers in Pediatrics, 9. https://doi.org/10.3389/fped.2021.595506

Goetz, L. H., & Schork, N. J. (2018). Personalized medicine: motivation, challenges, and progress. Fertility and Sterility, 109(6), 952–963. https://doi.org/10.1016/j.fertnstert.2018.05.006

Gupta, N., Thakur, A., & Gautam, D. (2023). ROLE OF ULTRASOUND AS PROGNOSTIC INDICATOR DURING PRONSETI CORRECTION. International Journal of Current Pharmaceutical Research, 43–46. https://doi.org/10.22159/ijcpr.2023v15i4.3023

Jing, X., Min, H., Gong, Y., Biondich, P., Robinson, D., Law, T., & Gimbel, R. (2023). Ontologies applied in clinical decision support system rules: Systematic review. JMIR medical informatics, 11, e43053.

Kyriakides, G., & Margaritis, K. G. (2019). Hands-On Ensemble Learning with Python. Published by Packt Publishing Ltd. ISBN 978-1-78961-285-1

Maghfuri, H. B., Alshareef, A. A., & Alshareef, A. (2024). The efficacy of the ponseti method in the management of clubfoot: a systematic review. Cureus, 16(1).

Malhotra, R., Mohapatra, A., Arora, G., Choudhury, P., Joshi, H., & Patel, P. (2018). Ponseti Technique for the Management of Congenital Talipes Equinovarus in a Rural Set-Up in India: Experience of 356 Patients. Children, 5(4), 49. https://doi.org/10.3390/children5040049

Melin, P., Sánchez, D., & Castillo, O. (2023). Interval Type-3 Fuzzy Inference System design for medical classificationusing genetic algorithms. Axioms, 13(1), 5. https://doi.org/10.3390/axioms13010005

Mohan, N. R., Singh, N. a. K., Kumar, N. D., Singh, N. S., Singh, N. A., Kushwaha, N. N. S., & Abbas, M. B. (2023). Does age and start of Ponseti treatment affect the functional outcome in club foot: A comparative study. Asian Journal of Medical Sciences, 14(4), 32–36. https://doi.org/10.3126/ajms.v14i4.50370

Punia, S. K., Kumar, M., Stephan, T., Deverajan, G. G., & Patan, R. (2021). Performance Analysis of Machine Learning Algorithms for Big Data Classification. International Journal of E-health and Medical Communications, 12(4), 60–75. https://doi.org/10.4018/ijehmc.20210701.oa4

Umoh U and Edidiong E. (2017). An Interval Type-2 Fuzzy Inference Framework for Short-Term Electric Load Forecasting in Nigeria. 3rd International Conference and Exhibition (OWSD – BIU

Umoh, U., Inyang, U. G., & Nyoho, E. E. (2019). Interval Type-2 Fuzzy Logic for Fire Outbreak Detection. International Journal on Soft Computing, Artificial Intelligence and Applications (Online)/International Journal on Soft Computing, Artificial Intelligence and Applications, 8(3), 27–46. https://doi.org/10.5121/ijscai.2019.8303

Valdez, F., Castillo, O., & Melin, P. (2025). A Bibliometric review of Type-3 fuzzy Logic Applications. Mathematics, 13(3), 375. https://doi.org/10.3390/math13030375

Walter, C., Sachsenmaier, S., Wünschel, M., Teufel, M., & Götze, M. (2020). Clubfoot treatment with Ponseti method—parental distress during plaster casting. Journal of Orthopaedic Surgery and Research, 15(1).

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