Neural FCA: Exploring Interpretability and Efficiency in Classification Tasks

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Abstract

This report investigates the application of Neural Formal Concept Analysis (FCA) for binary classification tasks, using the UCI Acute Inflammations dataset. Neural FCA is a hybrid approach that integrates Formal Concept Analysis with neural network architectures, providing an interpretable machine learning model. The study examines two binarization strategies for the temperature attribute, compares concept selection metrics (F1 score vs. accuracy), and evaluates the impact of activation functions (ReLU, Leaky ReLU, and Hyperbolic Tangent) on model performance. Additionally, Neural FCA is benchmarked against traditional classifiers, such as Logistic Regression and Random Forest, to evaluate its efficiency and predictive accuracy. The results demonstrate that Neural FCA can achieve high F1 scores, with improved interpretability, but its computational complexity makes it less efficient compared to modern machine learning methods.

1 Introduction

Formal Concept Analysis (FCA) is a mathematical framework for exploring binary relationships within datasets, organizing them into concept lattices that expose inherent structures. Neural FCA integrates FCA with neural networks, utilizing these lattices to guide network design. The primary benefit of Neural FCA is its interpretability, as it provides insights into the relationships between features and predicted outcomes.

The UCI Acute Inflammations dataset is a medical dataset that includes patient data used to predict two diseases: bladder inflammation (cystitis) and nephritis (inflammation of the kidney). The dataset consists of 120 rows, each representing a patient's symptoms, including temperature, nausea, lumbar pain, urine pushing, micturition pains, and burning sensations in the urethra.

The study aims to:

- Evaluate binarization methods for the temperature attribute.
- Compare two concept selection metrics: F1 score and accuracy.
- Investigate the impact of activation functions on Neural FCA performance.
- Benchmark Neural FCA against traditional classifiers, like Logistic Regression and Random Forest.

2 Dataset Description

2.1 Overview

The UCI Acute Inflammations dataset is a collection of patient records, including six features (five binary and one numerical) and two target variables (bladder inflammation and nephritis). The dataset consists of 120 instances, split evenly between positive and negative samples for both targets.

- **Instances**: 120 rows (patients)
- **Features**: 6 attributes, 5 binary (e.g., nausea, lumbar pain) and 1 continuous (temperature)
- **Targets**:

  - **Bladder Inflammation (Cystitis)**: Binary classification (0 = no, 1 = yes)
  - **Nephritis**: Binary classification (0 = no, 1 = yes)

2.2 Features

1. **Temperature of Patient**: This numerical feature indicates the patient's body temperature in the range [35.5, 41.5] Celsius, crucial for identifying fever-related conditions.

2. **Occurrence of Nausea**: Binary feature ("yes"/"no") indicating whether the patient experienced nausea.

3. **Lumbar Pain**: Binary feature ("yes"/"no") indicating the presence of lower back pain.

4. **Urine Pushing**: Binary feature ("yes"/"no") indicating the continuous need for urination.

5. **Micturition Pains**: Binary feature ("yes"/"no") indicating painful urination.

6. **Burning Sensation in Urethra**: Binary feature ("yes"/"no") indicating burning, itching, or swelling around the urethra.

2.3 Targets

- **Bladder Inflammation (Cystitis)**: 60 positive and 60 negative samples.

- **Nephritis**: 50 positive and 70 negative samples.

The balanced nature of the dataset provides a controlled environment for testing classification models.

3 Methodology

3.0.1 Temperature Distribution

To better understand the binarization strategy for the **temperature** feature, the distribution of temperature values is shown below. This visual representation helps explain the thresholds chosen for both the binary and trinary binarization strategies.

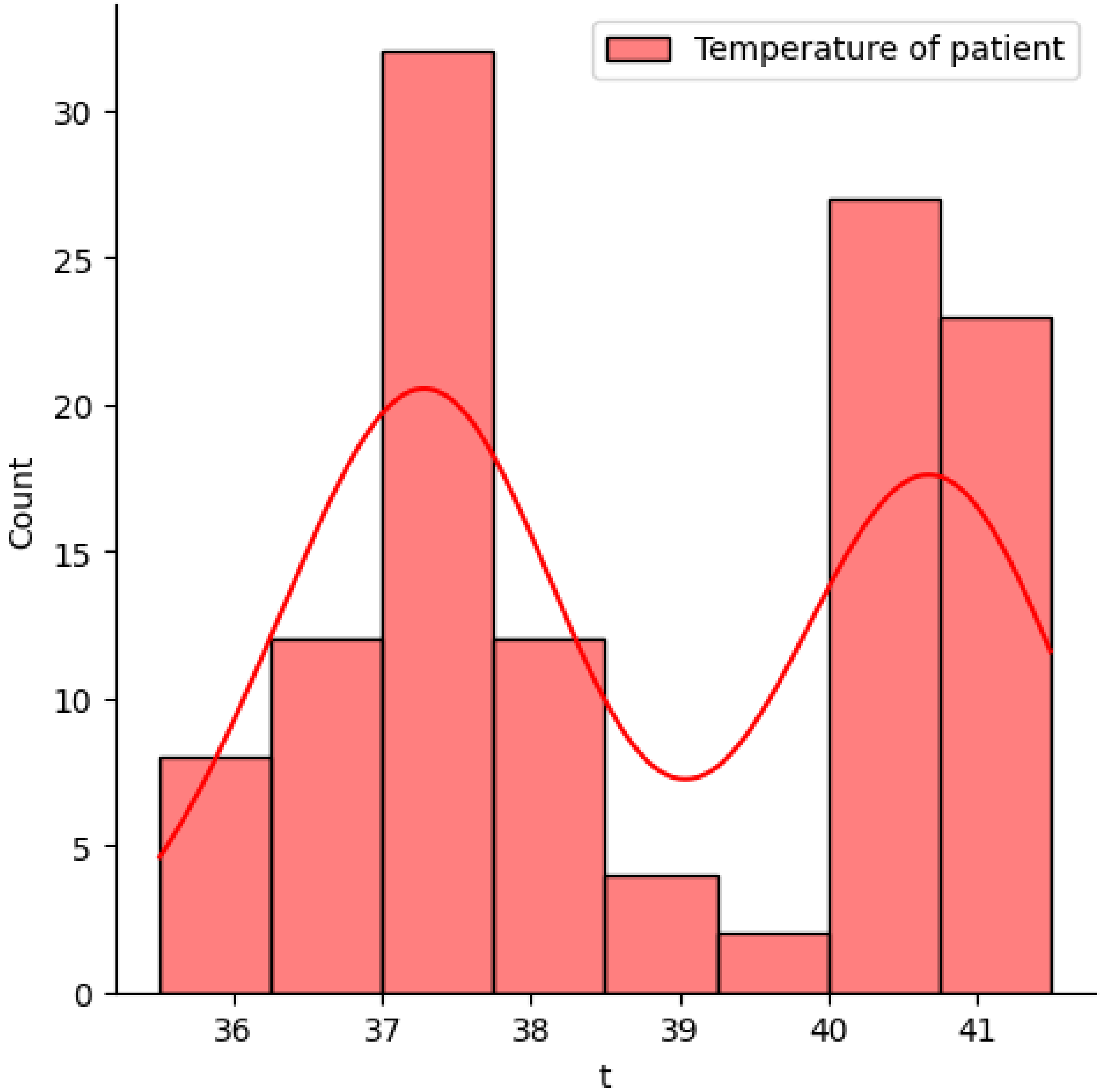

Figure 1: Temperature distribution of patients in the dataset.

3.1 Binarization Strategies

Handling the **temperature** feature, two binarization strategies were applied:

1. **Dichromatic scale Binarization**:

    - Temperature is less then or equal to 38: Categorized as "Normal" (0)
    - Temperature is greater then 38: Categorized as "Fever" (1)

    This strategy simplifies the temperature feature into a binary attribute, inspired by the World Health Organization's definition of fever.

2. **Ordinal Scale Binarization**:

    - Temperature is less then or equal to 36.5: Categorized as "Normal"
    - Temperature is less then or equal to 37.5: Categorized as "Normal" or "Elevated"
    - Temperature is less then or equal to 41.5: Categorized as "Normal" or "Elevated" or "Fever"

    This approach captures intermediate states.

3.2 Concept Lattice Construction

To construct the **Formal Context**, the dataset was represented as a binary matrix, where rows correspond to patients and columns correspond to features. The **Concept Lattice** is a hierarchical structure of formal concepts that capture relationships among attributes. Formal concepts are defined by their extents (objects) and intents (attributes).

3.3 Concept Selection Metrics

Two metrics were used for selecting the best concepts:

- **F1 Score**: Combines precision and recall, making it an ideal metric for imbalanced datasets.
- **Accuracy**: Measures the overall correctness of the model but may not provide insights into the performance on minority classes.

3.4 Neural FCA Architecture

Neural networks were built using the following structure:

- **Nodes**: Represent formal concepts derived from the concept lattice.
- **Edges**: Represent relationships between concepts based on lattice connections.
- **Activation Functions**: ReLU, Leaky ReLU, and Tanh were tested to assess their impact on model performance.

3.5 Comparative Classifiers

Traditional classifiers were implemented for comparison:

- Logistic Regression
- Random Forest
- Decision Tree
- XGBoost
- K-Nearest Neighbors
- Naive Bayes

These models were trained using default parameters to provide a benchmark for Neural FCA.

4 Results

4.1 Neural FCA Performance

The F1 scores for each implementation are summarized in the table below:

Model	Target attribute	Binarization Type	Best Concept Metric	Activation Function	F1 Score
1	Bladder Inflammation	Binary	F1 Score	ReLU	0.93
2	Nephritis	Binary	F1 Score	ReLU	0.86
3	Bladder Inflammation	Ordinal	F1 Score	ReLU	0.78
4	Nephritis	Ordinal	F1 Score	ReLU	0.875
5	Bladder Inflammation	Binary	Accuracy	ReLU	0.57
6	Nephritis	Binary	Accuracy	ReLU	0.875
7	Bladder Inflammation	Ordinal	Accuracy	ReLU	0
8	Nephritis	Ordinal	Accuracy	ReLU	0.875
9	Bladder Inflammation	Binary	F1 Score	Leaky ReLU	1
10	Nephritis	Binary	F1 Score	Leaky ReLU	1
11	Bladder Inflammation	Binary	F1 Score	Hyperbolic Tangent	1
12	Nephritis	Binary	F1 Score	Hyperbolic Tangent	1
13	Bladder Inflammation	Ordinal	F1 Score	Leaky ReLU	1
14	Nephritis	Ordinal	F1 Score	Leaky ReLU	1
15	Bladder Inflammation	Ordinal	F1 Score	Hyperbolic Tangent	1
16	Nephritis	Ordinal	F1 Score	Hyperbolic Tangent	1

Table 1: F1 Score for each model using different target attributes, binarization types, activation functions, and concept selection method.

The models using **F1 score as the concept selection metric** consistently outperformed those using **accuracy**. Additionally, models with **Leaky ReLU and Tanh** activations achieved perfect F1 scores, outperforming those with **ReLU**.

4.1.1 Neural Network Visualizations

The following neural network visualizations illustrate the weighted connections between formal concepts for each model. These visualizations highlight the most influential relationships between features and the predicted outcomes.

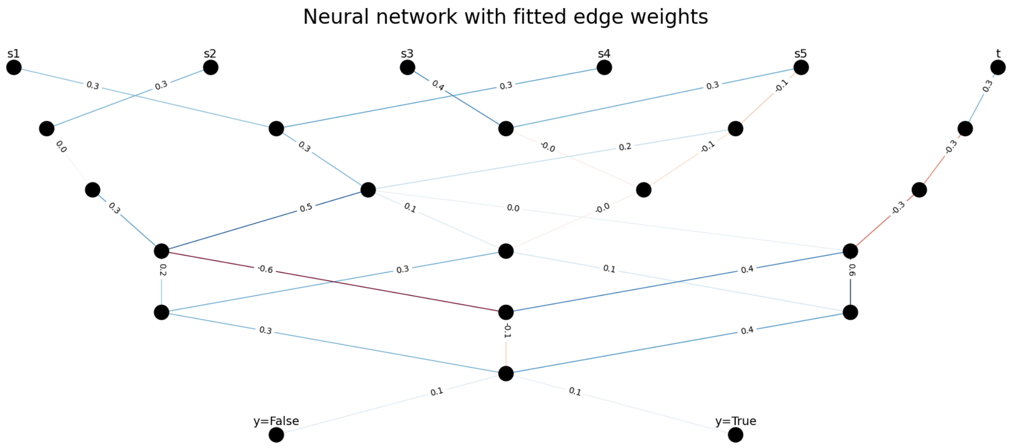

Figure 2: Neural network for Model 1 (Dichotomic scale, F1-score to select best concepts, ReLU activation and target attribute Bladder Inflammation).

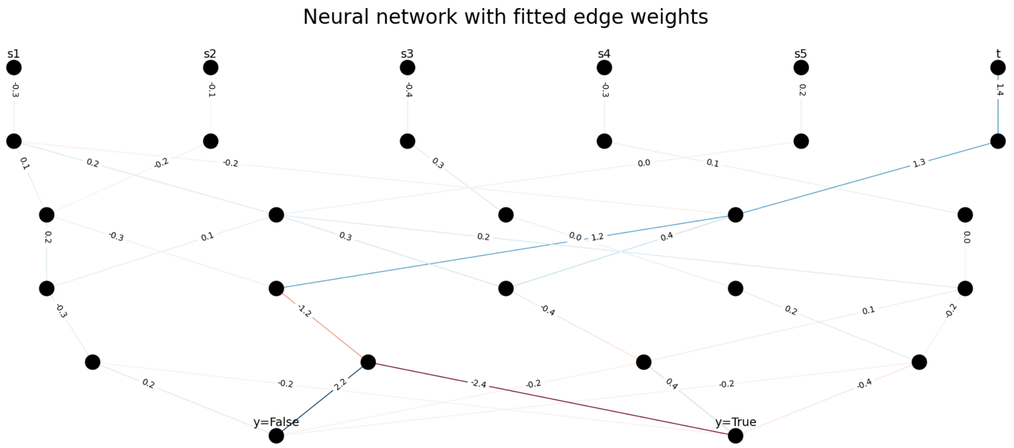

Figure 3: Neural network for Model 2 (Dichotomic scale, F1-score to select best concepts, ReLU activation and target attribute Nephritis).

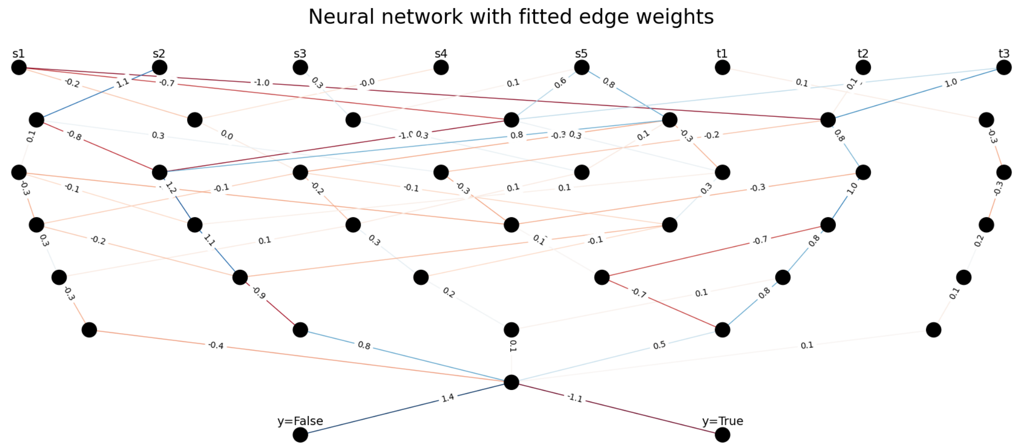

Figure 4: Neural network for Model 3 (Ordinal scale, F1-score to select best concepts, ReLU activation and target attribute Bladder Inflammation).

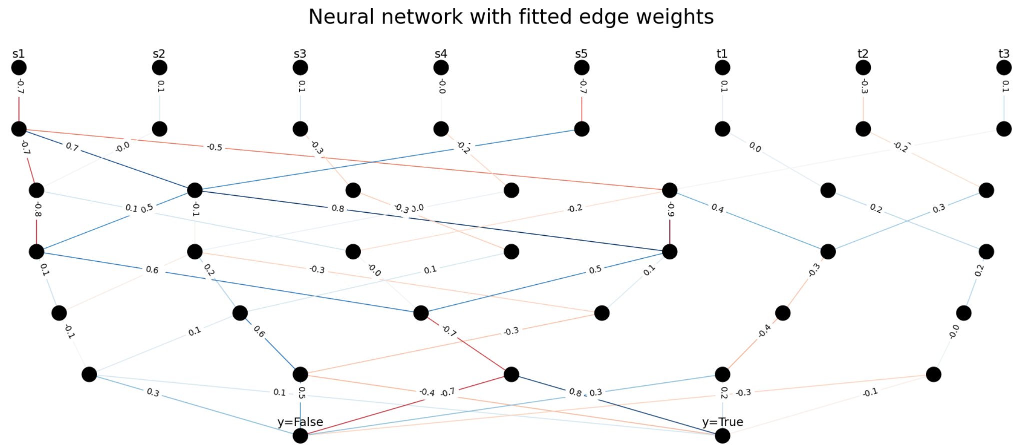

Figure 5: Neural network for Model 4 (Ordinal scale, F1-score to select best concepts, ReLU activation and target attribute Nephritis).

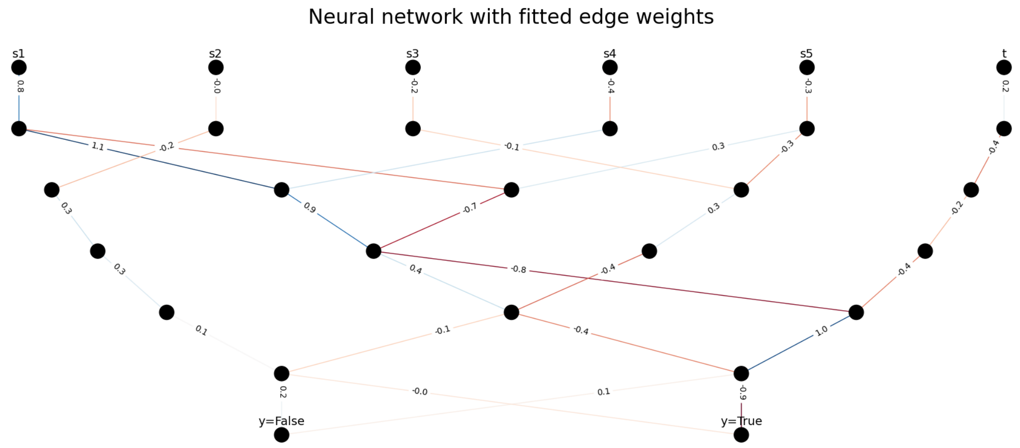

Figure 6: Neural network for Model 5 (Dichotomic scale, accuracy to select best concepts, ReLU activation and target attribute Bladder Inflammation).

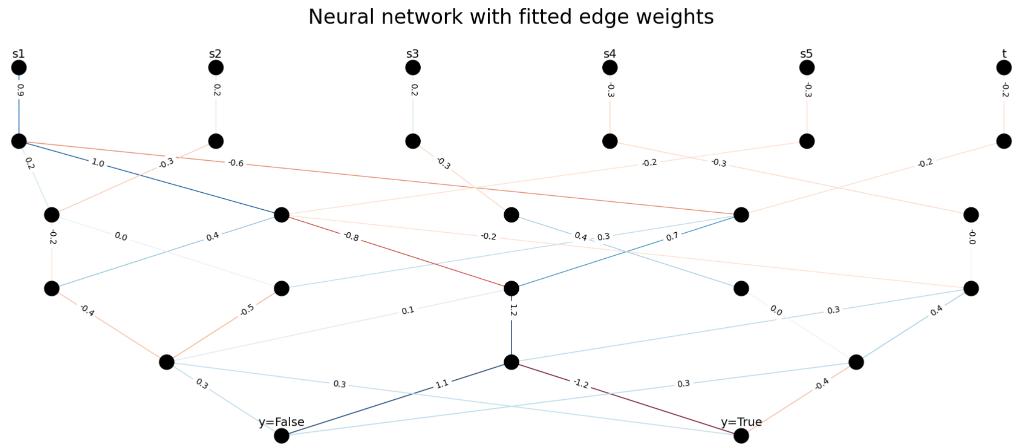

Figure 7: Neural network for Model 6 (Dichotomic scale, accuracy to select best concepts, ReLU activation and target attribute Nephritis).

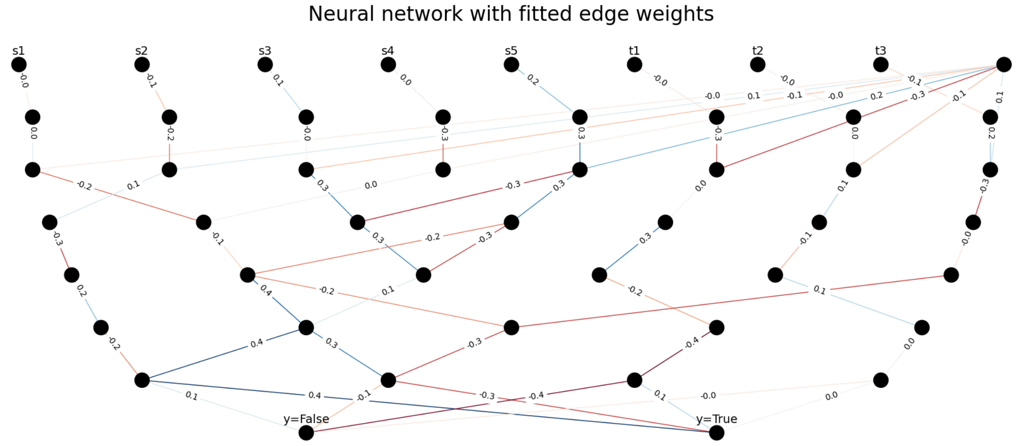

Figure 8: Neural network for Model 7 (Ordinal scale, accuracy to select best concepts, ReLU activation and target attribute Bladder Inflammation).

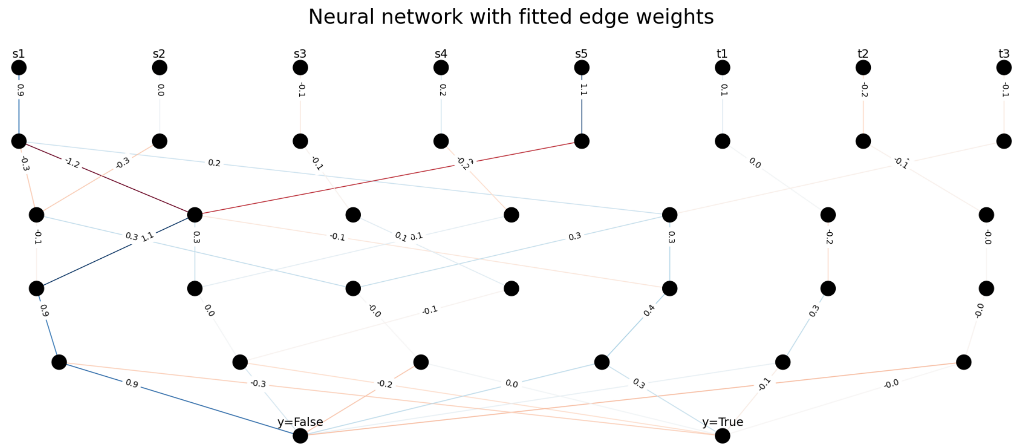

Figure 9: Neural network for Model 8 (Ordinal scale, accuracy to select best concepts, ReLU activation and target attribute Nephritis).

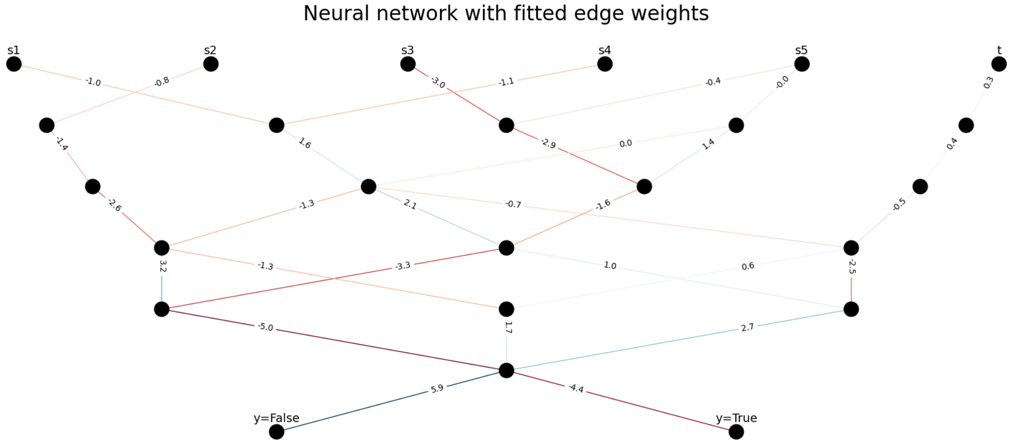

Figure 10: Neural network for Model 9 (Dichotomic scale, F1-score to select best concepts, Leaky ReLU activation and target attribute Bladder Inflammation).

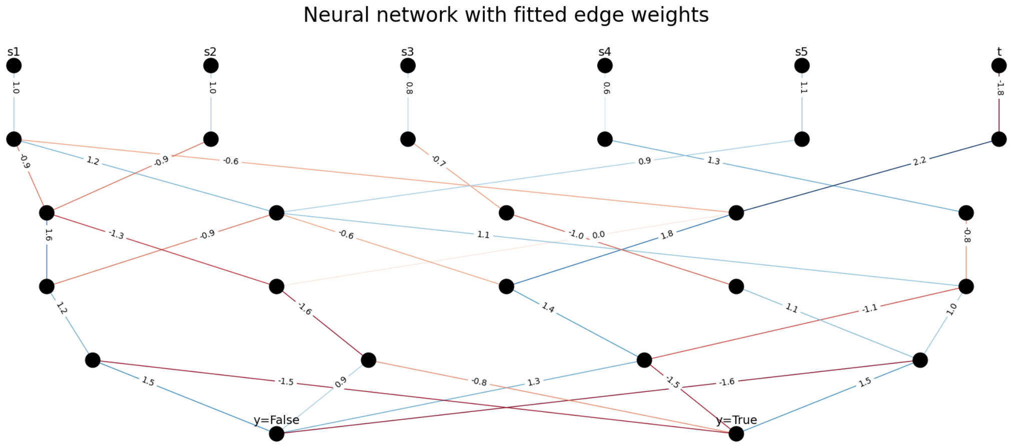

Figure 11: Neural network for Model 10 (Dichotomic scale, F1-score to select best concepts, Leaky ReLU activation and target attribute Nephritis).

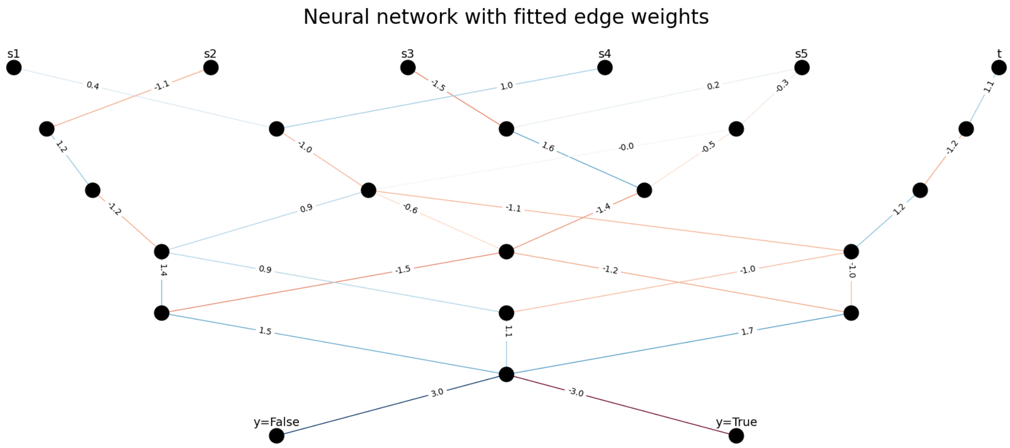

Figure 12: Neural network for Model 11 (Dichotomic scale, F1-score to select best concepts, hyperbolic tangent activation and target attribute Bladder Inflammation).

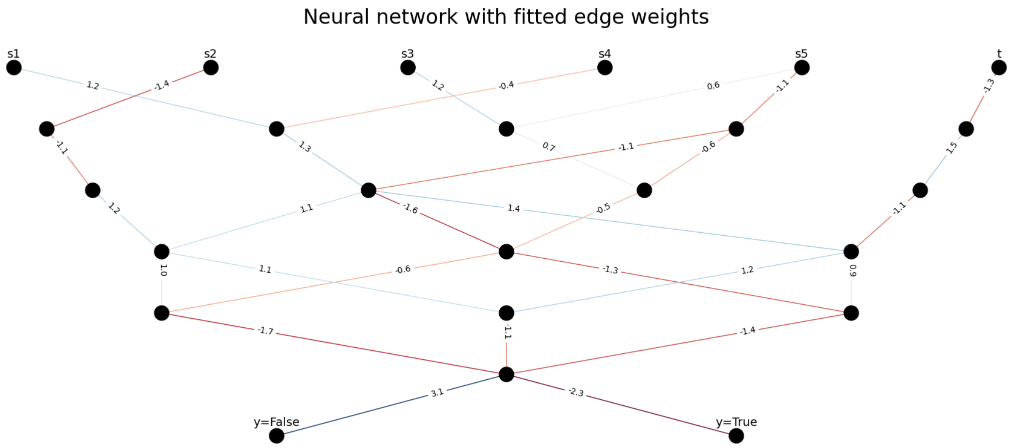

Figure 13: Neural network for Model 12 (Dichotomic scale, F1-score to select best concepts, hyperbolic tangent activation and target attribute Nephritis).

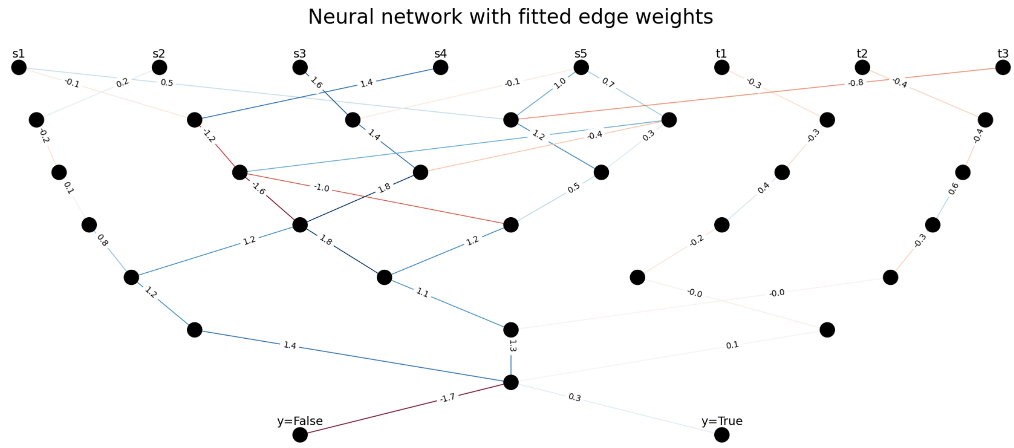

Figure 14: Neural network for Model 13 (Ordinal scale, F1-score to select best concepts, Leaky ReLU activation and target attribute Bladder Inflammation).

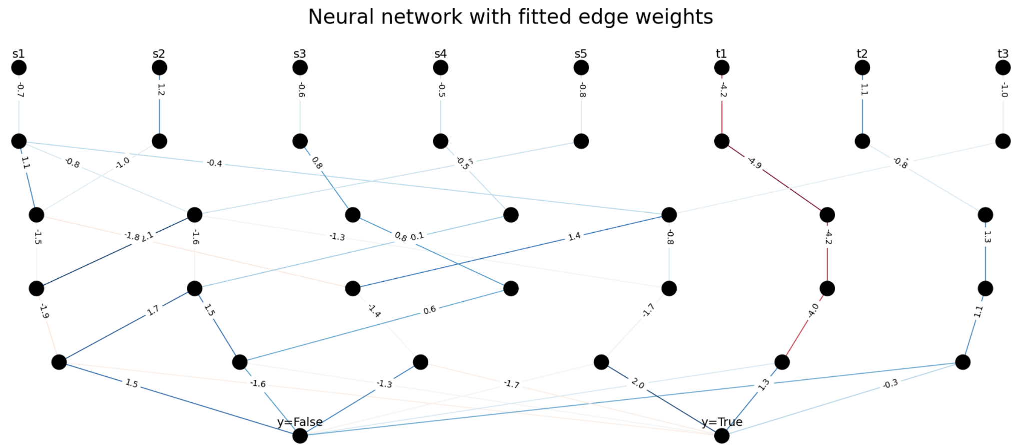

Figure 15: Neural network for Model 14 (Ordinal scale, F1-score to select best concepts, Leaky ReLU activation and target attribute Nephritis).

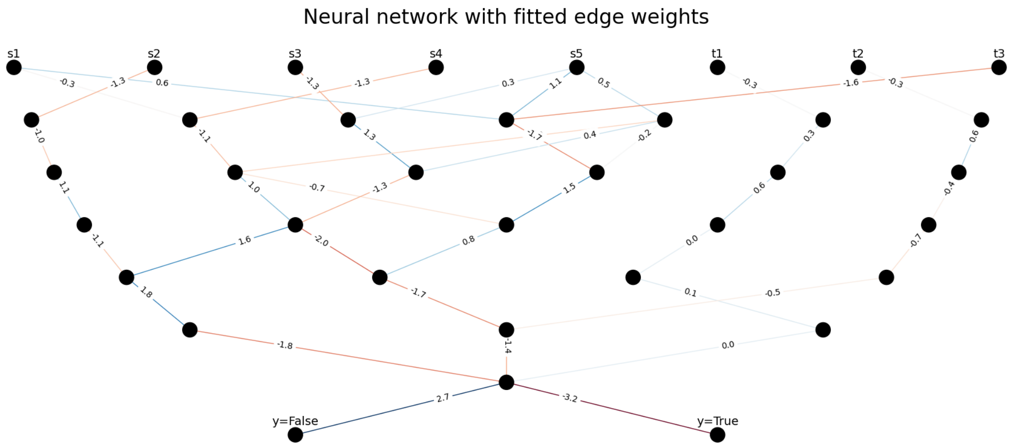

Figure 16: Neural network for Model 15 (Ordinal scale, F1-score to select best concepts, hyperbolic tangent activation and target attribute Bladder Inflammation).

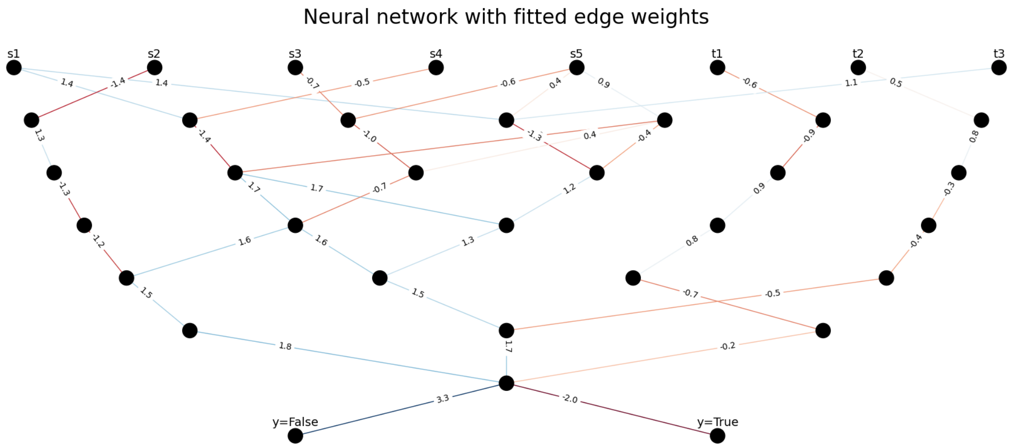

Figure 17: Neural network for Model 16 (Ordinal scale, F1-score to select best concepts, hyperbolic tangent activation and target attribute Nephritis).

4.2 Comparison with State-of-the-Art Approaches

Traditional classifiers like Logistic Regression and Random Forest achieved **F1 scores of 1.0**. However, these methods executed much faster than Neural FCA due to the absence of lattice construction and node relationship management. Neural FCA demonstrated the potential for interpretability, but the increased computational cost makes it less efficient for larger datasets.

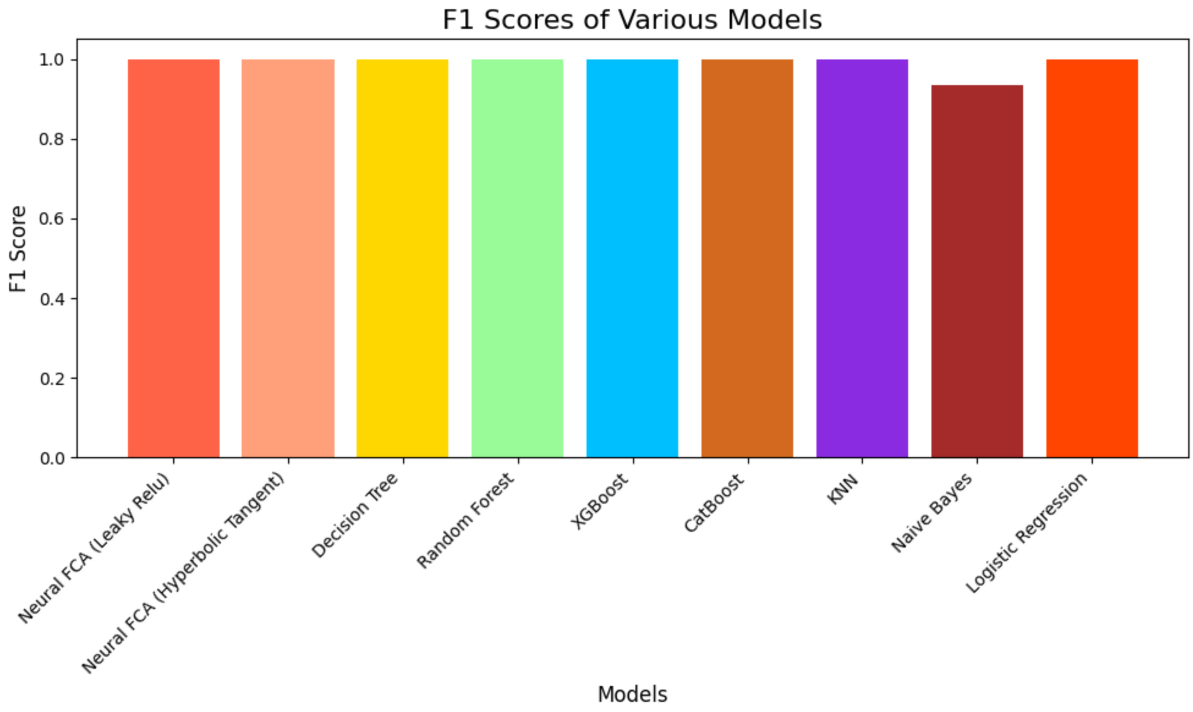

Figure 18: F1 score of Neural FCA against State-of-the-Art Approaches).

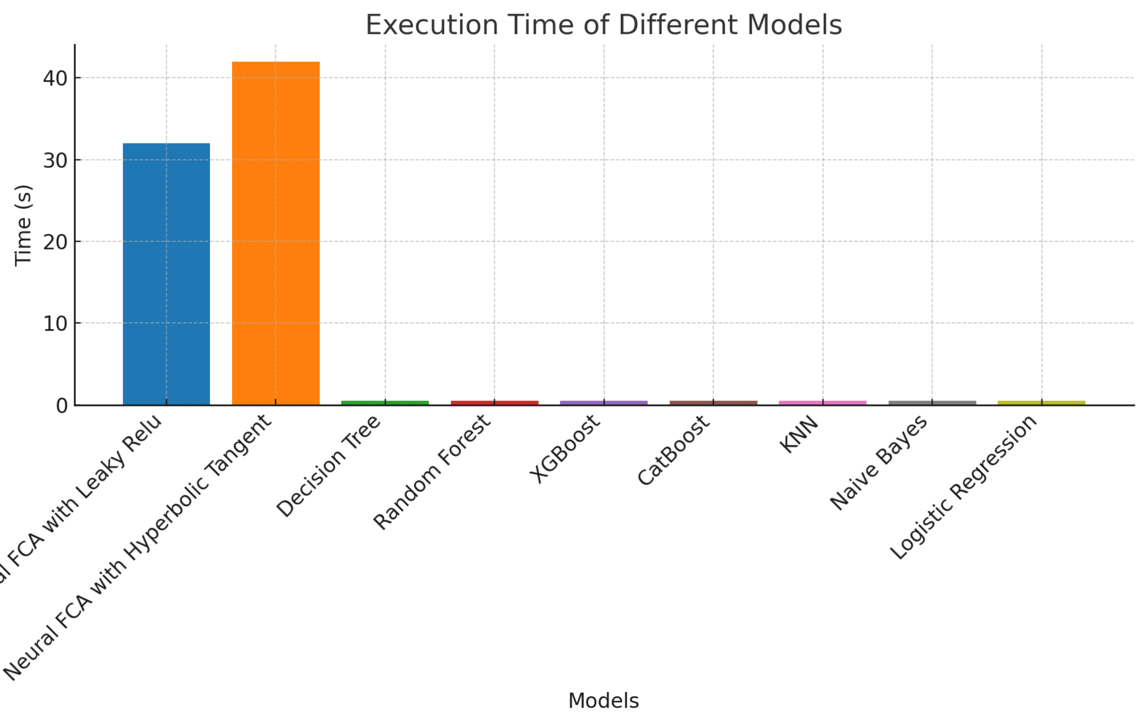

Figure 19: Time performance of Neural FCA against State-of-the-Art Approaches).

4.3 Insights from Weighted Neural Networks

Visualization of the neural network's **weighted edges** provided valuable insights into feature importance:

- **Temperature**: Had a strong influence on both targets, indicating its critical role in diagnosing fever-related conditions.
- **Lumbar Pain**: Was particularly significant for predicting **Nephritis**, highlighting its relevance to kidney-related symptoms.
- **Urine Pushing and Micturition Pains**: Were crucial for **Bladder Inflammation** prediction.

5 Discussion

Neural FCA provided excellent interpretability through **concept lattices** and visualizations, which offered a deeper understanding of the relationships between attributes and target outcomes. The results underscore the importance of the **activation function** choice, with Leaky ReLU and Tanh significantly improving performance over ReLU.

However, the method's **computational complexity** limits scalability for larger datasets. Further optimizations, such as more efficient lattice construction or pruning of irrelevant concepts, could enhance performance.

6 Conclusion

Neural FCA strikes a unique balance between **interpretability** and **performance**, making it a promising approach for applications requiring explainable models. Despite its slower runtime compared to modern machine learning methods, it offers potential in domains where interpretability and feature importance are key.