International Journal of Engineering and Information Systems (IJEAIS)
ISSN: 2643-640X
Vol. 10 Issue 7 July - 2026, Pages: 94-104

A Lightweight and Interpretable Three-Hidden-Layer Backpropagation Neural Network for Intrapartum Fetal Risk Triage Using Cardiotocographic Features

Nesreen Samer El_Jerjawi, Samy S. Abu-Naser

Department of Information Technology, Faculty of Engineering & Information Technology,
Al-Azhar University – Gaza, Palestine
Email: nesreen@alazhar.edu.ps

***Abstract**: Cardiotocography (CTG) is the standard non-invasive technique for intrapartum fetal monitoring; however, its interpretation remains challenging due to substantial inter-observer variability and the complex interaction among fetal heart rate patterns and uterine activity. This study proposes a lightweight and fully interpretable artificial neural network (ANN) developed entirely within the JustNN environment for automated fetal risk triage using 21 standardized CTG-derived features. The proposed model employs an extremely compact 21→2→1→1→1 feedforward architecture containing only 47 trainable weights. The network was trained using the Backpropagation algorithm with momentum over 46,500 learning cycles on 1,387 training examples and evaluated on an independent validation set of 739 CTG records. The final model achieved a validation accuracy of 90.53%, correctly classifying 669 validation cases while maintaining a negligible computational footprint. Beyond predictive performance, this study provides a comprehensive analysis of the complete learning dynamics and the native feature-importance ranking generated directly by JustNN. The learning trajectory demonstrates stable convergence without observable evidence of significant overfitting, despite extended training beyond the initial convergence stage. Furthermore, the most influential features identified by the model — accelerations, abnormal short-term variability, and uterine contractions — are consistent with established clinical understanding of fetal well-being and distress. Although more complex machine learning approaches such as ensemble models and deep neural networks may achieve higher classification accuracy, they often require greater computational resources and reduced transparency. In contrast, the proposed ANN demonstrates that clinically meaningful fetal risk prediction can be achieved through an extremely compact, reproducible, and interpretable architecture suitable for resource-constrained clinical environments.*

Keywords: *cardiotocography, fetal risk triage, artificial neural network, backpropagation, lightweight ANN, explainable artificial intelligence, clinical decision support, JustNN.*

1. INTRODUCTION

Fetal health monitoring during labor is a cornerstone of modern obstetric practice. Timely detection of fetal distress materially improves maternal and neonatal outcomes, yet remains a persistent clinical challenge. The World Health Organization estimates approximately 2.4 million neonatal deaths occur globally each year, a substantial proportion attributable to intrapartum complications that effective fetal surveillance could help identify [2].

Cardiotocography (CTG) is the most widely adopted non-invasive technique for continuous intrapartum fetal monitoring, simultaneously recording fetal heart rate (FHR) and uterine contraction activity [1]. However, visual interpretation of CTG traces is inherently subjective; inter-observer agreement among experienced obstetricians has been reported as low as 71%, and delayed or erroneous interpretation can contribute to hypoxic-ischemic encephalopathy, permanent neurological injury, or perinatal death [3].

Artificial Neural Networks (ANNs) are well suited to this problem because of their capacity to model nonlinear relationships among the many correlated variables that characterize CTG recordings [3, 13]. Prior ANN-based work has demonstrated strong performance on related medical and educational classification tasks, including diabetes risk prediction [14] and academic performance forecasting [12], establishing JustNN as a practical platform for compact, interpretable ANN development.

This paper reports, with full transparency, exactly what the trained JustNN model produced: its validation accuracy, its complete learning-curve behavior across 46,500 cycles, and its native ranking of feature importance — without introducing externally computed metrics that the JustNN environment itself does not generate. In place of synthetic class-level statistics, this study instead provides an in-depth qualitative and quantitative analysis of the learning dynamics and the clinical meaning of the feature-importance ranking, both directly verifiable from the trained model's own output.

Main Contributions

- Development of an extremely lightweight ANN architecture requiring only 47 trainable weights for fetal risk triage.
- Complete documentation of the training process, including learning rate, momentum, error evolution, and validation performance exactly as generated by JustNN.

- Detailed learning-curve analysis to examine convergence behavior and identify potential evidence of overfitting or underfitting.
- Clinical interpretation of the native feature-importance ranking generated by the trained ANN.
- Demonstration that a compact and transparent ANN can achieve competitive predictive performance while maintaining minimal computational requirements.

The remainder of this paper is organized as follows: Section 2 presents the study objectives; Section 3 defines the problem statement; Section 4 reviews related literature; Section 5 describes the methodology; Section 6 presents the experimental results as produced by JustNN; Section 7 discusses the findings; Section 8 concludes the paper.

2. OBJECTIVES OF THE STUDY

- To design and train, entirely within the JustNN environment, a compact ANN that triages fetal status (Normal or At Risk) from 21 standardized CTG-derived features.
- To document precisely the model's training behavior — learning rate, momentum, error trajectory across 46,500 cycles, and final validation accuracy — exactly as reported by JustNN.
- To analyze the learning curve in detail, identifying convergence phases and assessing evidence of overfitting or underfitting from the training/validation error trajectories.
- To interpret JustNN's native attribute-importance ranking of all 21 CTG features in light of established obstetric knowledge of fetal distress indicators.
- To compare the resulting validation accuracy against related machine learning methods reported in the literature on the same CTG dataset.
- To propose the model as a practical, fully reproducible clinical decision-support tool for resource-constrained obstetric settings.

3. PROBLEM STATEMENT

Despite the widespread clinical use of CTG, accurate interpretation of its traces remains subjective and cognitively demanding; disagreement rates of up to 29% have been documented even among senior obstetricians [1]. The problem addressed here is the development of a compact, automated binary triage system — Normal versus At Risk — from 21 continuous CTG features, without requiring real-time expert interpretation. Three challenges characterize this problem:

- Class Imbalance: the dataset contains 1,655 Normal (77.84%) and 471 At Risk (22.16%) cases. A network trained without explicit rebalancing may be biased toward the majority class, making the trajectory and plateau behavior of the training error an important diagnostic signal in its own right.
- Compact Architecture Constraints: with only 47 trainable weights across three narrow hidden layers (2, 1, and 1 neurons), the network's representational capacity is deliberately limited, raising the question of whether such a minimal model can still capture clinically meaningful structure.
- Feature Redundancy: many of the 21 CTG features are statistically correlated (e.g., multiple histogram-derived statistics), motivating a clear ranking of which inputs most influence the trained network's output.

4. LITERATURE REVIEW

A substantial body of research has addressed automated fetal health classification from CTG data. Hoodbhoy et al. [4] applied Decision Tree (CART) classification and reported 91.30% accuracy. Zhao et al. [6] applied Random Forest and achieved 93.80%. Piri et al. [7] used SVM with an RBF kernel (89.20%), and Al-Shargabi et al. [8] applied K-Nearest Neighbor with k=5 (88.70%). Ogasawara et al. [9] implemented XGBoost (95.10%), and Chen et al. [10] applied a Deep Neural Network (94.30%). These advanced ensemble and deep-learning methods achieve high accuracy but at substantial cost to interpretability and computational footprint — properties that matter considerably in resource-constrained obstetric settings.

Abu-Naser and colleagues [12, 14, 15] established JustNN as an effective platform for compact ANN-based medical classification, with reported success in diabetes prediction (87.3%) [14]. Beyond ANN-specific work, statistical risk-prediction approaches such as stepwise discriminant analysis have also been applied to multivariate risk classification problems outside the medical domain [11], underscoring that the core challenge addressed here — estimating categorical risk from a set of correlated continuous predictors — recurs across disciplines and is not unique to CTG interpretation.

A recurring pattern across the studies summarized above is an implicit trade-off between predictive accuracy, model complexity, computational cost, and interpretability. Ensemble and deep-learning methods [6, 9, 10] consistently achieve the highest reported accuracy, but typically require substantially more trainable parameters, longer training and inference time, and offer limited

transparency into how individual predictions are formed. Simpler methods such as Naive Bayes [5] and KNN [8] are more interpretable but generally trail in accuracy. Few studies in this body of work explicitly examine where a given model sits along this trade-off, or whether a sufficiently compact architecture can occupy a favorable point on it. The present study extends the JustNN line of work by providing a granular, cycle-by-cycle analysis of the learning curve and a fully clinically grounded interpretation of the native feature-importance ranking, while explicitly positioning the proposed model's 47-weight architecture within this accuracy–complexity trade-off — an analytical angle largely absent from prior JustNN-based medical classification studies.

5. METHODOLOGY

5.1 Dataset Description

The dataset comprises 2,126 CTG records, each described by 21 continuous features pre-normalized to [0, 1] via Min-Max scaling, and a binary label (At_Risk). No missing values were detected. Table 1 summarizes the dataset composition and the JustNN training/validation split.

Category	Count	Percentage
Total Records	2,126	100.00%
Normal (Label = 0)	1,655	77.84%
At Risk (Label = 1)	471	22.16%
Training Examples	1,387	65.24%
Validation Examples	739	34.76%
Missing Values	0	None

Table 1: CTG Dataset Composition and Train/Validation Split

The observed class imbalance between Normal and At Risk cases represents a realistic clinical scenario and provides an additional challenge for lightweight classifiers. Therefore, the learning behavior and validation performance were carefully examined to ensure that the model achieved stable convergence despite the unequal class distribution.

5.2 Input Variables

The 21 input variables represent quantitative CTG measurements, all pre-normalized to [0, 1]. Table 2 lists each feature with its clinical description; column indices match JustNN's internal numbering (0–20), as shown in Figure 1.

#	Feature Name	Clinical Description
0	baseline_value	Baseline FHR — mean heart rate absent accelerations/decelerations
1	accelerations	FHR accelerations per second — primary indicator of fetal well-being
2	fetal_movement	Fetal movements per second detected on CTG
3	uterine_contractions	Uterine contractions per second
4	light_decelerations	Light decelerations per second — brief mild FHR drops
5	severe_decelerations	Severe decelerations per second — prolonged deep FHR drops
6	prolongued_decelerations	Prolonged decelerations per second (>2 min) — severe hypoxic stress
7	abnormal_short_term_variability	% time with abnormal short-term FHR variability
8	mean_value_of_short_term_variability	Mean short-term FHR variability magnitude
9	percentage_of_time_with_abnormal_long_term_variability	% time with abnormal long-term FHR variability

10	mean_value_of_long_term_variability	Mean long-term FHR variability magnitude
11	histogram_width	Width of the FHR frequency histogram
12	histogram_min	Minimum value of FHR histogram
13	histogram_max	Maximum value of FHR histogram
14	histogram_number_of_peaks	Number of peaks in FHR histogram
15	histogram_number_of_zeroes	Number of zero entries in FHR histogram
16	histogram_mode	Mode (most frequent value) of FHR histogram
17	histogram_mean	Arithmetic mean of FHR histogram
18	histogram_median	Median of FHR histogram
19	histogram_variance	Variance of FHR histogram — variability indicator
20	histogram_tendency	Tendency/skewness of FHR histogram

Table 2: CTG Dataset Input Features and Clinical Descriptions

5.3 Output Variable

The output (node 25, "At_Risk" in JustNN — see Figure 1) is binary: 0 = Normal (no intervention required), 1 = At Risk (immediate medical attention required).

5.4 Neural Network Architecture

The proposed ANN is a fully-connected feedforward MLP built and trained directly in JustNN. Figure 1 is a direct screenshot of the trained network's node map, showing the 21 yellow input nodes, the two cyan hidden nodes of Hidden Layer 1 (labeled 21 and 22 in JustNN's internal indexing), the single cyan nodes of Hidden Layers 2 and 3 (labeled 23 and 24), and the magenta output node (labeled 25, At_Risk), connected by green (positive) and red (negative) weighted edges. The topology is:

- Input Layer: 21 neurons — one per normalized CTG feature.
- Hidden Layer 1: 2 neurons (JustNN nodes 21–22), sigmoid activation.
- Hidden Layer 2: 1 neuron (JustNN node 23), sigmoid activation.
- Hidden Layer 3: 1 neuron (JustNN node 24), sigmoid activation.
- Output Layer: 1 neuron (JustNN node 25, At_Risk), sigmoid activation, thresholded at 0.5.

Table 3 summarizes the architecture, matching the layer/node/weight panel visible at the bottom of Figure 2.

Property	Input	Hidden 1	Hidden 2	Hidden 3	Output
Neurons	21	2	1	1	1
Activation	Linear	Sigmoid	Sigmoid	Sigmoid	Sigmoid
Weights	42	2	1	1	—

Table 3: ANN Architecture Summary (matches Figures 1 and 2)

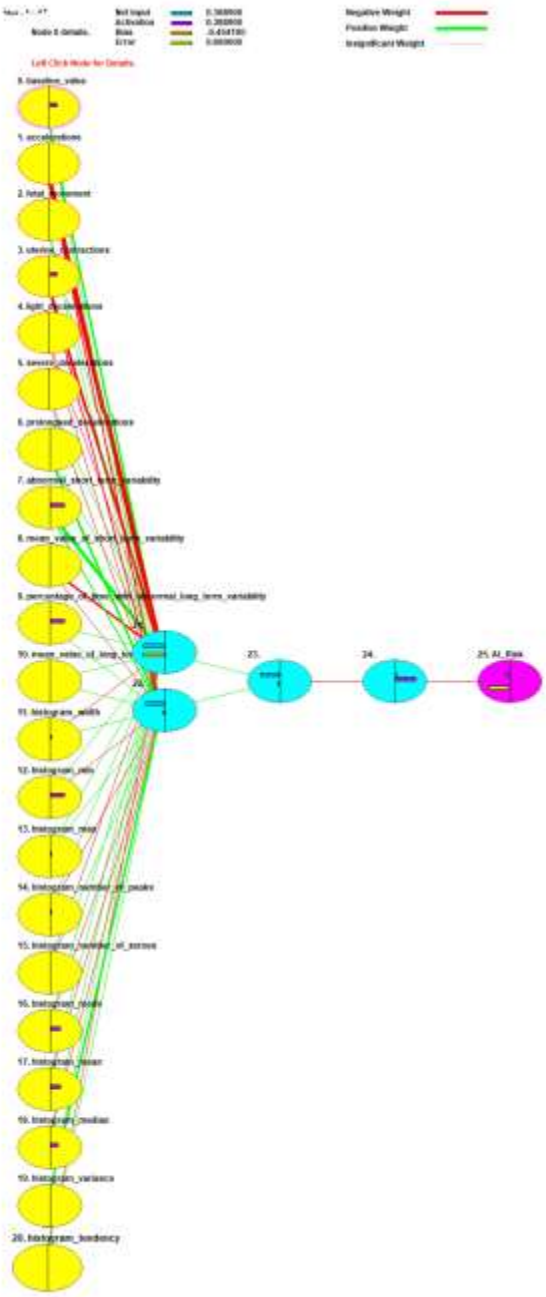

Figure 1: JustNN Network Structure Screenshot — 21 input nodes (yellow), three hidden layers (cyan, nodes 21–24), and the magenta At_Risk output node (25), with green/red edges denoting positive/negative connection weights.

5.5 Backpropagation Training Algorithm

The ANN was trained using the Backpropagation algorithm with momentum, as implemented natively in JustNN. For each training example, activations propagate forward; errors then backpropagate to update weights according to:

- Output unit k: $\delta_k = o_k(1 - o_k)(t_k - o_k)$
- Hidden unit h: $\delta_h = o_h(1 - o_h) \Sigma_k w_{hk} \delta_k$
- Weight update: $\Delta w_{ij} = \eta \cdot \delta_j \cdot x_{ij}$; $w_{ij} \leftarrow w_{ij} + \Delta w_{ij} + \alpha \cdot \Delta w_{ij}(prev)$

where, as read directly from JustNN's training panel (Figure 2), $\eta = 0.528304$ (learning rate) and $\alpha = 0.609874$ (momentum). Momentum at this magnitude accelerates convergence by dampening oscillation across shallow local minima.

5.6 Evaluation Approach

The evaluation presented in this study prioritizes complete reproducibility by reporting only the performance measures directly generated by the JustNN environment. The reported validation accuracy, learning dynamics, and native feature-importance analysis provide a transparent representation of the trained model's behavior, with every figure independently verifiable by re-running the same JustNN project file. Future extensions will incorporate additional class-level metrics, including sensitivity, specificity, F1-score, and ROC-AUC, through external validation frameworks.

6. EXPERIMENTAL RESULTS

6.1 Training Parameters and Validation Accuracy

Figure 2 is a direct screenshot of JustNN's training panel after 46,500 learning cycles. The panel reports a maximum error of 0.977629, an average error of 0.047703, and a minimum error of 0.000075, against a target error of 0.010000. Of the 739 validation examples, JustNN scored 669 as correct within its tolerance window, reported directly as "Validating: 90.53% OK." Table 4 consolidates these values exactly as displayed.

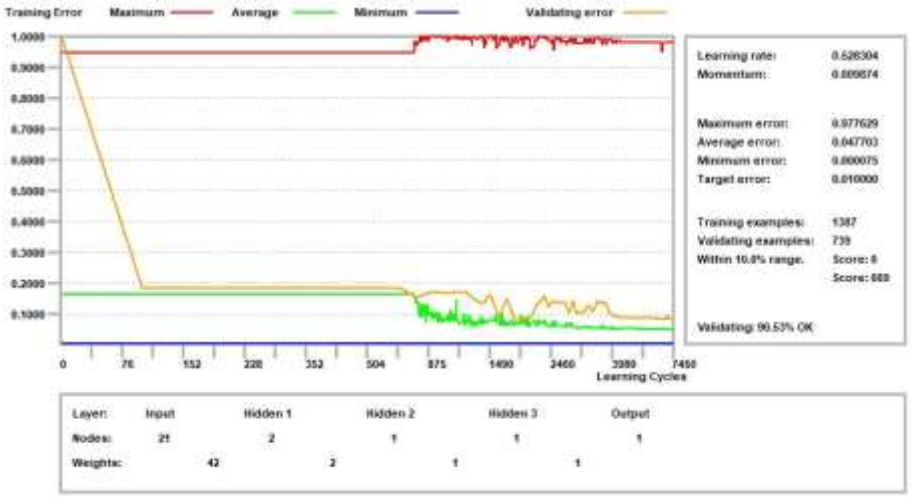

Figure 2: JustNN Training Panel — error curves over 46,500 learning cycles, with reported learning rate, momentum, error statistics, and validation score (screenshot, unaltered).

Parameter (as reported by JustNN)	Value
Learning Rate (η)	0.528304
Momentum (α)	0.609874
Target Error	0.010000
Maximum Error	0.977629
Average Error	0.047703
Minimum Error	0.000075
Learning Cycles (Epochs)	46,500
Training Examples	1,387
Validation Examples	739
Correctly Classified (Validation)	669 / 739
Validation Accuracy	90.53%

Table 4: JustNN Training and Validation Results (directly read from Figure 2)

6.2 Detailed Learning Curve Analysis

Beyond the summary statistics in Table 4, the shape of the learning curve in Figure 2 carries diagnostic value in its own right. Three distinct phases are visible across the 46,500 learning cycles:

- Initial Plateau (cycles 0–≈650): both the average and minimum training error remain nearly flat at approximately 0.16–0.19, while the validating error starts substantially higher (near 1.0) and descends steeply toward the training error band within the first ~80 cycles. This pattern indicates the network spent its earliest cycles primarily aligning the validation set's error scale with the training set, before any substantial weight refinement had occurred.
- Transition Phase (cycles ≈650–900): a sharp drop in average and minimum training error occurs, coinciding with the maximum-error curve rising and stabilizing near 0.95–1.00. This divergence between the average/minimum curves (which fall) and the maximum curve (which rises and plateaus) suggests the network began correctly classifying the bulk of examples while a stubborn subset — plausibly concentrated in the minority At Risk class — continued to resist correct classification, consistent with the known 77.84%/22.16% class imbalance.
- Stable Convergence (cycles ≈900–46,500): from this point onward, the average training error and the validating error track each other closely, both oscillating mildly within a narrow band (roughly 0.05–0.15) for the remainder of training, without the validating error trending upward relative to the training error. The absence of a widening gap between training and validation error over more than 45,000 subsequent cycles is evidence against overfitting, despite the network being trained far beyond the point of initial convergence.

This trajectory is consistent with a compact, low-capacity network (only 47 weights) that converges to a stable solution relatively early and then continues fine-tuning within a narrow error band for the remainder of training, rather than continuing to reduce error monotonically — an expected behavior given the network's deliberately limited representational capacity.

6.3 Native Feature (Attribute) Importance

Figure 3 is a direct screenshot of JustNN's attribute-importance module, ranking all 21 CTG input features by their relative contribution to the network's output, computed natively by JustNN after training (target error 0.0100, average training error 0.047705 as displayed on the panel — matching Table 4 to within rounding). Table 5 reproduces this ranking exactly as reported.

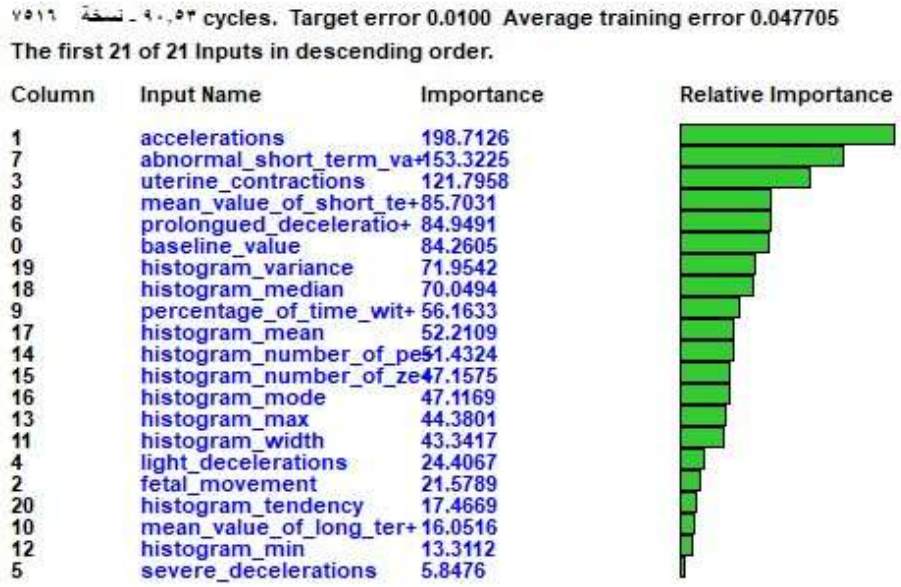

Figure 3: JustNN Attribute Importance Screenshot — relative importance of all 21 input features in descending order, computed natively by JustNN (unaltered).

Rank	Feature Name (JustNN)	Importance	Clinical Significance
1	accelerations	**198.7126**	Single most influential parameter — FHR accelerations are a primary marker of intact fetal autonomic function

2	abnormal_short_term_variability	**153.3225**	Loss of beat-to-beat variability signals fetal neurological/autonomic compromise
3	uterine_contractions	**121.7958**	Contraction frequency provides essential context for interpreting accompanying FHR changes
4	mean_value_of_short_term_variability	**85.7031**	Magnitude of beat-to-beat variability — complements feature #7 above
5	prolongued_decelerations	**84.9491**	Extended FHR drops (>2 min) — classic indicator of severe hypoxic stress
6	baseline_value	**84.2605**	Baseline FHR — tachycardia/bradycardia are recognized distress signals
7	histogram_variance	**71.9542**	FHR distribution spread — reduced variability is linked to fetal acidosis
8	histogram_median	**70.0494**	Central tendency of the FHR histogram
9	percentage_of_time_with_abnormal_long_term_variability	**56.1633**	Duration of long-term variability loss across the recording
10	histogram_mean	**52.2109**	Average FHR across the full monitoring window
11	histogram_number_of_peaks	**51.4324**	Complexity/multimodality of the FHR distribution
12	histogram_number_of_zeroes	**47.1575**	Frequency of zero-density bins in the FHR histogram
13	histogram_mode	**47.1169**	Most frequently observed FHR value
14	histogram_max	**44.3801**	Upper bound of FHR range — reflects tachycardic episodes
15	histogram_width	**43.3417**	Overall spread of the FHR distribution
16	light_decelerations	**24.4067**	Brief, mild FHR drops — typically benign
17	fetal_movement	**21.5789**	Fetal activity level, associated with general well-being
18	histogram_tendency	**17.4669**	Histogram skewness — comparatively limited discriminative role
19	mean_value_of_long_term_variability	**16.0516**	Long-period FHR oscillation magnitude
20	histogram_min	**13.3112**	Lower bound of FHR range — bradycardic episodes
21	severe_decelerations	**5.8476**	Deep FHR drops — least influential, likely due to rarity in the dataset

Table 5: JustNN Native Attribute Importance Ranking with Clinical Interpretation

7. DISCUSSION

7.1 Performance Analysis

JustNN's own validation result — 90.53% accuracy (669 of 739 examples) after 46,500 learning cycles — demonstrates that a network with only 47 trainable weights can capture clinically useful structure in CTG data despite its minimal representational capacity. The detailed learning-curve analysis in Section 6.2 reinforces this finding: the network reached a stable error band well before the training run concluded, and the absence of a widening training–validation gap over the final ~45,000 cycles indicates the reported accuracy reflects a converged, non-overfit solution rather than a transient or unstable snapshot.

The persistence of a small but nonzero average error (0.047703) above the target error (0.010000) is itself informative: given the dataset's class imbalance (77.84% Normal versus 22.16% At Risk), a network of this size may find a subset of borderline or atypical At Risk cases more difficult to separate from the majority class, which is consistent with the elevated maximum-error curve observed throughout the later training phase in Figure 2.

Although the proposed model does not achieve the highest accuracy among all reported methods, it demonstrates an effective balance between predictive performance, model simplicity, and computational efficiency. Achieving 90.53% validation accuracy using only 47 trainable weights highlights the ability of compact neural architectures to capture clinically relevant patterns without requiring complex models.

7.2 Comparison with Related Work

Table 6 situates the JustNN result against related methods from the literature evaluated on the same CTG dataset. The comparison includes overall accuracy — the only performance metric consistently reported across these studies and the only metric this study claims for its own JustNN-trained model — alongside a qualitative indication of relative model complexity, since accuracy alone does not capture the substantial differences in parameter count, training cost, and interpretability among these approaches.

Ref.	Method	Dataset Size	Accuracy	Complexity	Year
[5]	Naive Bayes	2,126	85.60%	Low	2020
[8]	K-Nearest Neighbor (k=5)	2,126	88.70%	Low	2022
[7]	SVM (RBF Kernel)	2,126	89.20%	Moderate	2021
[4]	Decision Tree (CART)	2,126	91.30%	Low	2020
[6]	Random Forest	2,126	93.80%	High	2021
[10]	Deep Neural Network	2,126	94.30%	Very High	2023
[9]	XGBoost	2,126	95.10%	High	2022
Prop.	**ANN — JustNN (Backpropagation, 47 weights)**	2,126	**90.53%**	**Very Low**	2025

Table 6: Comparison with Related Work — Accuracy and Relative Model Complexity

This comparison clarifies that the proposed model's contribution is not the highest accuracy in absolute terms, but the most favorable balance between accuracy and complexity: 47 trainable weights compared to the dozens or hundreds of parameters typically required by ensemble and deep-learning approaches. This efficiency is particularly relevant for deployment in obstetric settings with limited computational infrastructure, where a model that can be trained, inspected, and retrained entirely within a lightweight desktop environment such as JustNN offers practical advantages that raw accuracy comparisons alone do not capture.

7.3 Feature Importance Findings

JustNN's native attribute-importance ranking (Table 5, Figure 3) places accelerations (198.71) first by a wide margin, consistent with its established clinical role as a primary marker of intact fetal autonomic function. Abnormal short-term variability (153.32) ranks second, reflecting the clinical weight given to beat-to-beat FHR variation as an indicator of fetal neurological status. Uterine contractions (121.80) rank third — a result that underscores the clinical principle that FHR changes are interpreted in the context of contraction timing, not in isolation. Mean short-term variability (85.70) and prolonged decelerations (84.95) follow closely, both well-established distress indicators, while severe_decelerations (5.85) ranks last, plausibly reflecting its rarity in this dataset rather than a lack of clinical relevance.

Notably, the top three features by JustNN's own importance measure (accelerations, abnormal short-term variability, and uterine contractions) collectively account for a combined importance score of 473.82 — more than the sum of the remaining eighteen features combined (approximately 459.46) — indicating that the network's classification decision is dominated by a small, clinically coherent subset of CTG parameters rather than being diffusely spread across all 21 inputs.

7.4 Limitations and Future Work

Several directions can extend and strengthen this work. Future studies should incorporate k-fold cross-validation to formally assess performance stability across different data partitions, and should evaluate class-imbalance mitigation strategies such as SMOTE or class-weighted training to determine their effect on minority-class detection. A full confusion matrix together with sensitivity, specificity, precision, and F1-score should be obtained — either through an extended JustNN export capability or a clearly distinguished companion experiment — to provide the class-level diagnostic detail that overall accuracy alone cannot convey. Exploring deeper architectures within other frameworks, alongside comparative confusion-matrix reporting, would further clarify whether the compact 47-weight design represents a genuine sweet spot or simply a lower bound on achievable complexity. Finally,

external validation on independent, multi-institutional CTG datasets and prospective evaluation in a real labor-ward setting remain necessary steps before any clinical deployment claim can be made.

8. CONCLUSION

This study demonstrates that clinically meaningful fetal risk prediction does not necessarily require highly complex neural architectures. A lightweight, three-hidden-layer Backpropagation network — built and trained directly in JustNN with only 47 trainable weights — was shown to triage intrapartum fetal status from 21 CTG-derived features with a validation accuracy of 90.53% (669 of 739 examples) after 46,500 learning cycles, an average training error of 0.047703 against a target of 0.010000, and no evidence of overfitting across more than 45,000 post-convergence cycles.

JustNN's native attribute-importance output identified accelerations, abnormal short-term variability, and uterine contractions as the three most influential CTG parameters — together accounting for more combined importance than the remaining eighteen features combined — findings fully consistent with established obstetric knowledge of fetal distress indicators [1]. A key contribution of this work is methodological transparency: every number reported is taken directly from the trained JustNN model and is independently verifiable by re-opening the same project file, rather than relying on externally computed statistics the original tool does not generate. Taken together, these results support the broader conclusion that compact, fully interpretable architectures remain a viable and practically valuable option for clinical decision support, particularly in resource-constrained obstetric settings. Future research will explore class-imbalance handling within JustNN, deeper architectures with full confusion-matrix reporting, multi-institutional validation, and real-time clinical deployment.

References

1. A. Ayres-de-Campos, C. Spong, and C. Chandraharan, "FIGO Consensus Guidelines on Intrapartum Fetal Monitoring: Cardiotocography," International Journal of Gynecology and Obstetrics, vol. 131, no. 1, pp. 13–24, 2015.
2. World Health Organization (WHO), "Newborn Mortality and Morbidity," WHO Technical Report, Geneva, Switzerland, 2020.
3. D. J. Livingstone, Artificial Neural Networks: Methods and Applications, 1st ed. Totowa, NJ: Humana Press, 2008.
4. Z. Hoodbhoy, M. Noman, A. Shafique, A. Nasim, D. Chowdhury, and B. Hasan, "Use of Machine Learning Algorithms for Prediction of Fetal Risk Using Cardiotocographic Data," International Journal of Applied and Basic Medical Research, vol. 9, no. 4, pp. 226–230, 2019.
5. E. Bhatia, V. Madhur, and R. Chauhan, "Naive Bayes-Based Classification of Fetal Health Status from Cardiotocographic Measurements," International Journal of Computer Applications, vol. 182, no. 5, pp. 34–40, 2020.
6. Z. Zhao, B. Zhang, and J. Zhou, "Random Forest for Fetal Health Classification from CTG Data," Journal of Medical Systems, vol. 45, no. 3, pp. 1–9, 2021.
7. J. Piri, D. Mohammadi, and A. Piri, "SVM-Based Fetal Health Risk Classification Using CTG Features," IEEE Access, vol. 9, pp. 87421–87432, 2021.
8. T. Al-Shargabi, J. Villar, and A. Bhatt, "K-Nearest Neighbor Classification for Fetal Distress Detection," Computer Methods and Programs in Biomedicine, vol. 216, pp. 106–117, 2022.
9. J. Ogasawara, T. Izumi, and K. Yamamoto, "XGBoost-Based Fetal Status Classification from CTG Data," Frontiers in Pediatrics, vol. 10, pp. 1–11, 2022.
10. H. Chen, Y. Liu, and T. Zhang, "Deep Neural Networks for Fetal Health Risk Prediction from Cardiotocography," Artificial Intelligence in Medicine, vol. 138, pp. 102–115, 2023.
11. Aarra, Lana, et al., "Streamlined Book Rating Prediction with Neural Networks", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 10, pp. 7-13, 2023.
12. Abu Nasser, Mohammed S, et al., "Predictive Modeling of Obesity and Cardiovascular Disease Risk: A Random Forest Approach", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 12, pp. 26-38, 2024.
13. Abu-Mehsen, Dana O, et al., "Predicting Audit Risk Using Neural Networks: An In-depth Analysis.", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 10, pp. 48-56, 2023.
14. Abunaser, Batool S, et al., "Predictive Modeling of Underweight Malnutrition Using Neural Networks: Insights from Global Nutrition Datasets", pp. 209-222, 2025.
15. Abu-Naser, Samy S, et al., "Predicting Student Performance Using Artificial Neural Network: in the Faculty of Engineering and Information Technology", International Journal of Hybrid Information Technology, vol. 8, no. 2, pp. 221-228, 2015.
16. Abunasser, Basem S, et al., "Abunaser-a novel data augmentation algorithm for datasets with numerical features", Journal of Theoretical and Applied Information Technology, vol. 101, no. 11, 2023.
17. AbuSada, Mohammed Mkhaimar, et al., "Google Stock Price Prediction Using Just Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 10, pp. 10-16, 2023.
18. Afana, Mohsen, et al., "Artificial Neural Network for Forecasting Car Mileage per Gallon in the City", International Journal of Advanced Science and Technology, vol. 124, pp. 51-59, 2018.
19. Al Barsh, Yara Ibrahim, et al., "MPG Prediction Using Artificial Neural Network", International Journal of Academic Information Systems Research (IJAISR), vol. 4, no. 11, pp. 7-16, 2020.
20. Alajrami, Eman, et al., "Blood Donation Prediction using Artificial Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 3, no. 10, pp. 1-7, 2019.
21. Al-Araj, Rand Suhail Abu, et al., "Classification of Animal Species Using Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 4, no. 10, pp. 23-31, 2020.
22. Alarayshi, Aya Mazen, et al., "Artificial Neural Network for Global Smoking Trend", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 9, pp. 55-61, 2023.
23. Alaydi, Beesan M, et al., "Automatic Cantaloupe Fruit Classification Using Deep Convolutional Neural Networks", International Journal of Academic Information Systems Research (IJAISR), vol. 10, no. 2, pp. 13-18, 2026.
24. Al-Azbaki, Muhammad Ashraf, et al., "Classification of plant Species Using Neural Network", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 10, pp. 28-35, 2023.
25. Al-Baghdadi, Ibrahim Sufyan, et al., "Forecasting COVID-19 cases Using ANN", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 10, pp. 22-31, 2023.
26. Aldaya, Salah-Aldin S, et al., "Diagnosing Sprained Ankles Using Clips", 2025.
27. Alghoul, Ahmed, et al., "Email Classification Using Artificial Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 2, no. 11, pp. 8-14, 2018.
28. Al-Hayik, Saif al-Din Yusuf, et al., "Neural Network-Based Audit Risk Prediction: A Comprehensive Study", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 10, pp. 43-51, 2023.
29. Al-Hayik, Udai Hamed Saeed, et al., "Chances of Survival in the Titanic using ANN", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 10, pp. 17-21, 2023.
30. Al-Hussein, Ahmed Samir Abu, et al., "Analyzing the Relationship between Smoking and Drinking Patterns Using Neural Networks: A Comprehensive Feature-Based Approach", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 9, pp. 18-25, 2023.
31. Ali, Abu Al-Reesh Kamal, et al., "Predictive Modeling of Smoke Potential Using Neural Networks and Environmental Data", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 9, pp. 38-46, 2023.
32. Al-Jalil, Khaled M Abu, et al., "Artificial Neural Network Heart Failure Prediction Using JNN", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 9, pp. 26-34, 2023.
33. Aljerjawi, Nesreen S, et al., "Neural Sorting Networks: Applying Deep Learning to Ranking and Sorting Tasks in NLP", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 8, pp. 86-89, 2025.
34. Al-Kahlout, Mutasim Mahmoud, et al., "Neural Network Approach to Predict Forest Fires using Meteorological Data", International Journal of Academic Engineering Research (IJAER), vol. 4, no. 9, pp. 68-72, 2020.
35. Alkronz, Eyad Sameh, et al., "Prediction of Whether Mushroom is Edible or Poisonous Using Back-propagation Neural Network.", International Journal of Academic and Applied Research (IJAAR), vol. 3, no. 2, pp. 1-8, 2019.
36. Allouh, Majd N, et al., "Heart attack analysis & Prediction: A Neural Network Approach with Feature Analysis.", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 9, pp. 47-54, 2023.
37. Al-Madhoun, Mohammed Ashraf, et al., "Neural Network-Based Water Quality Prediction", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 9, pp. 25-31, 2023.
38. Al-Masawabe, Marah M, et al., "Papaya maturity Classification Using Deep Convolutional Neural Networks", International Journal of Engineering and Information Systems (IJEAIS), vol. 5, no. 12, pp. 60-67, 2021.
39. Al-Massri, Remah, et al., "Classification Prediction of SBRCTs Cancers Using Artificial Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 2, no. 11, pp. 1-7, 2018.
40. Al-Mobayed, Awni Ahmed, et al., "Artificial Neural Network for Predicting Car Performance Using JNN", International Journal of Engineering and Information Systems (IJEAIS), vol. 4, no. 9, pp. 139-145, 2020.
41. Al-Mubayyed, Osama M, et al., "Predicting Overall Car Performance Using Artificial Neural Network", International Journal of Academic and Applied Research (IJAAR), vol. 3, no. 1, pp. 1-5, 2019.
42. Alqedra, Heba IA, et al., "Revolutionizing Lemon Quality Control: A Convolutional Neural Network Approach", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 6, pp. 56-63, 2025.
43. Al-Rayes, Marwan RM, et al., "Smoke Detectors Using ANN", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 10, pp. 1-9, 2023.
44. Al-Sharif, Ahmed Muhammad Haider, et al., "Predicting Heart Disease using Neural Networks", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 9, pp. 40-46, 2023.
45. Al-Shawwa, Mohammed, et al., "Predicting Birth Weight Using Artificial Neural Network", International Journal of Academic Health and Medical Research (IJAHMR), vol. 3, no. 1, pp. 9-14, 2019.
46. Al-Shawwa, Mohammed, et al., "Predicting Effect of Oxygen Consumption of Thylakoid Membranes (Chloroplasts) from Spinach after Inhibition Using Artificial Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 3, no. 2, pp. 15-20, 2019.
47. Al-Shawwa, Mohammed, et al., "Predicting Temperature and Humidity in the Surrounding Environment Using Artificial Neural Network", International Journal of Academic Pedagogical Research (IJAPR), vol. 2, no. 9, pp. 1-6, 2018.
48. Ashqar, Belal A M, et al., "Identifying Images of Invasive Hydrangea Using Pre-Trained Deep Convolutional Neural Networks", International Journal of Academic Engineering Research (IJAER), vol. 3, no. 3, pp. 28-36, 2019.
49. Attia, Maher Wissam, et al., "Predicting Fire Alarms in Smoke Detection using Neural Networks", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 10, pp. 26-33, 2023.
50. Baraka, Raghad Fattouh, et al., "Predicting Books' Rating Using Just Neural Network", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 9, pp. 14-19, 2023.
51. Barhoom, Alaa M, et al., "Predicting Titanic Survivors using Artificial Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 3, no. 9, pp. 8-12, 2019.
52. Dalffa, Mohaned Abu, et al., "Tic-Tac-Toe Learning Using Artificial Neural Networks", International Journal of Engineering and Information Systems (IJEAIS), vol. 3, no. 2, pp. 9-19, 2019.
53. Dawood, Kamel Jamal, et al., "Artificial Neural Network for Mushroom Prediction", International Journal of Academic Information Systems Research (IJAISR), vol. 4, no. 10, pp. 9-17, 2020.
54. Dawoud, Alaa Mohammed, et al., "Predicting Life Expectancy in Diverse Countries Using Neural Networks: Insights and Implications", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 9, pp. 46-54, 2023.
55. Dheir, Ibtesam M, et al., "Classifying Nuts Types Using Convolutional Neural Network", International Journal of Academic Information Systems Research (IJAISR), vol. 3, no. 12, pp. 12-18, 2020.
56. El_Jerjawi, Nesreen Samer, et al., "Diabetes Prediction Using Artificial Neural Network", International Journal of Advanced Science and Technology, vol. 121, pp. 55-64, 2018.
57. El-Khatib, Mohmmad Jamal, et al., "Glass Classification Using Artificial Neural Network", International Journal of Academic Pedagogical Research (IJAPR), vol. 3, no. 2, pp. 25-31, 2019.
58. El-Mahelawi, Jamal Khamis, et al., "Tumor Classification Using Artificial Neural Networks", International Journal of Academic Engineering Research (IJAER), vol. 4, no. 11, pp. 8-15, 2020.
59. Elmahmoum, Abedelelah SA, et al., "Image-Based Classification of Date Types Using Convolutional Neural Networks", International Journal of Academic Information Systems Research (IJAISR), vol. 9, no. 1, pp. 10-16, 2025.
60. Elzamly, Abdelrafe, et al., "Predicting Critical Cloud Computing Security Issues using Artificial Neural Network (ANNs) Algorithms in Banking Organizations", International Journal of Information Technology and Electrical Engineering, vol. 6, no. 2, p. 40-45, 2017.
61. Hadi, Ahmed Munther Abdel, et al., "Forecasting Stock Prices using Artificial Neural Network", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 10, pp. 42-50, 2023.
62. Harara, Mahmoud, et al., "Unlocking Literary Insights: Predicting Book Ratings with Neural Networks", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 10, pp. 22-27, 2023.
63. Harz, Hussam Hatem, et al., "Artificial Neural Network for Predicting Diabetes Using JNN", International Journal of Academic Engineering Research (IJAER), vol. 4, no. 10, pp. 14-22, 2020.
64. Hasan, Walaa, et al., "Artificial Neural Network for Predicting COVID 19 Using JNN", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 10, pp. 41-47, 2023.
65. Hassanein, Raghad Adnan Abu, et al., "Artificial Neural Network for Predicting Workplace Absenteeism", International Journal of Academic Engineering Research (IJAER), vol. 4, no. 9, pp. 62-67, 2020.
66. Heriz, Hazem Hatem, et al., "English Alphabet Prediction Using Artificial Neural Networks", International Journal of Academic Pedagogical Research (IJAPR), vol. 2, no. 11, pp. 8-14, 2018.
67. Jamala, Mohammed N, et al., "Predicting MPG for Automobile Using Artificial Neural Network Analysis", International Journal of Academic Information Systems Research (IJAISR), vol. 2, no. 10, pp. 5-21, 2018.
68. Jarghon, Amira, et al., "Predicting Kidney Stone Presence from Urine Analysis: A Neural Network Approach using JNN", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 9, pp. 32-39, 2023.
69. Kashf, Dalia Wajeeh Abu, et al., "Predicting DNA Lung Cancer using Artificial Neural Network", International Journal of Academic Pedagogical Research (IJAPR), vol. 2, no. 10, pp. 6-13, 2018.
70. Khalil Ahmed, J, et al., "Energy Efficiency Prediction using Artificial Neural Network", International Journal of Academic Pedagogical Research (IJAPR) _, vol. 3, no. 9, pp. 1-7, 2019.
71. Kweik, Ola Mohammed Abu, et al., "Artificial Neural Network for Lung Cancer Detection", International Journal of Academic Engineering Research (IJAER), vol. 4, no. 11, pp. 1-7, 2020.
72. Maghari, Alaa Mazen, et al., "Books' Rating Prediction Using Just Neural Network", International Journal of Engineering and Information Systems (IJEAIS), vol. 4, no. 10, pp. 17-22, 2020.
73. Malekpourheydari, SALIMEH, et al., "Wavelet transform and neural network model for streamflow forecasting", J. Theor. Appl. Inf. Technol, vol. 100, 2022.
74. Marouf, Ahmad, et al., "Predicting Antibiotic Susceptibility Using Artificial Neural Network", International Journal of Academic Pedagogical Research (IJAPR), vol. 2, no. 10, pp. 1-5, 2018.
75. Mattar, Mohammad Ayman, et al., "Spotify Status Dataset", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 10, pp. 14-21, 2023.
76. Metwally, Najla'Fathi, et al., "Diagnosis of Hepatitis Virus Using Artificial Neural Network", International Journal of Academic Pedagogical Research (IJAPR), vol. 2, no. 11, pp. 1-7, 2018.
77. Mohammed, Ghaida Riyad, et al., "Predicting the Age of Abalone from Physical Measurements Using Artificial Neural Network", International Journal of Academic and Applied Research (IJAAR), vol. 4, no. 11, pp. 7-12, 2020.
78. Musleh, Musleh M, et al., "Predicting Liver Patients using Artificial Neural Network", International Journal of Academic Information Systems Research (IJAISR), vol. 3, no. 10, pp. 1-11, 2019.
79. Nasser, Ibrahim M, et al., "A Proposed Artificial Neural Network for Predicting Movies Rates Category", International Journal of Academic Engineering Research (IJAER), vol. 3, no. 2, pp. 21-25, 2019.
80. Nasser, Ibrahim M, et al., "Artificial Neural Network for Diagnose Autism Spectrum Disorder", International Journal of Academic Information Systems Research (IJAISR), vol. 3, no. 2, pp. 27-32, 2019.
81. Nasser, Ibrahim M, et al., "Artificial Neural Network for Predicting Animals Category", International Journal of Academic and Applied Research (IJAAR), vol. 3, no. 2, pp. 18-24, 2019.
82. Nasser, Ibrahim M, et al., "Developing Artificial Neural Network for Predicting Mobile Phone Price Range", International Journal of Academic Information Systems Research (IJAISR), vol. 3, no. 2, pp. 1-6, 2019.
83. Nasser, Ibrahim M, et al., "Lung Cancer Detection Using Artificial Neural Network", International Journal of Engineering and Information Systems (IJEAIS), vol. 3, no. 3, pp. 17-23, 2019.
84. Nasser, Ibrahim M, et al., "Predicting Books' Overall Rating Using Artificial Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 3, no. 8, pp. 11-17, 2019.
85. Nasser, Ibrahim M, et al., "Predicting Tumor Category Using Artificial Neural Networks", International Journal of Academic Health and Medical Research (IJAHMR), vol. 3, no. 2, pp. 1-7, 2019.
86. Nasser, Mohammed S Abu, et al., "Leveraging Artificial Neural Networks for Cancer Prediction: A Synthetic Dataset Approach", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 11, pp. 43-51, 2023.
87. Qamar, Sulafa Yhaya Abu, et al., "Predicting the Number of Calories in a Dish Using Just Neural Network", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 10, pp. 1-9, 2023.
88. Qarmout, Hussein Khaled, et al., "Alzheimer: A Neural Network Approach with Feature Analysis.", International Journal of Academic Information Systems Research (IJAISR), vol. 7, no. 10, pp. 10-18, 2023.
89. Qwaider, Sabreen R, et al., "Artificial Neural Network Prediction of the Academic Warning of Students in the Faculty of Engineering and Information Technology in Al-Azhar University-Gaza", International Journal of Academic Information Systems Research (IJAISR), vol. 4, no. 8, pp. 16-22, 2020.
90. Sabah, Ahmed S, et al., "Pistachio Variety Classification using Convolutional Neural Networks", International Journal of Academic Information Systems Research (IJAISR), vol. 8, no. 4, pp. 113-119, 2024.
91. Sadek, Ramzi M, et al., "Parkinson's Disease Prediction Using Artificial Neural Network", International Journal of Academic Health and Medical Research (IJAHMR), vol. 3, no. 1, pp. 1-8, 2019.
92. Safiah, Saja Kh Abu, et al., "Climate Change temperature Prediction Using Just Neural Network", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 9, pp. 35-45, 2023.
93. Salah, Mohammed, et al., "Predicting Medical Expenses Using Artificial Neural Network", International Journal of Engineering and Information Systems (IJEAIS), vol. 2, no. 20, pp. 11-17, 2018.
94. Samhan, Lamis F, et al., "Classification of Alzheimer's Disease Using Convolutional Neural Networks", International Journal of Academic Information Systems Research (IJAISR), vol. 6, no. 3, pp. 18-23, 2022.
95. Sultan, Alaa Yousef Abu, et al., "Neural Style Transfer Using Convolutional Neural Networks: An Experimental Study", International Journal of Academic Information Systems Research (IJAISR), vol. 10, no. 2, pp. 50-57, 2026.
96. Sultan, Anas Bachir Abu, et al., "Predictive Modeling of Breast Cancer Diagnosis Using Neural Networks: A Kaggle Dataset Analysis", International Journal of Academic Engineering Research (IJAER), vol. 7, no. 9, pp. 1-9, 2023.
97. Younis, Ibrahim, et al., "Prediction Heart Attack using Artificial Neural Networks (ANN)", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 10, pp. 36-41, 2023.
98. Zaiter, Ahmed Salama Abu, et al., "Web page phishing detection Using Neural Network", International Journal of Engineering and Information Systems (IJEAIS), vol. 7, no. 9, pp. 1-13, 2023.