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Article

Early Diagnosis Opportunities in Neonatal Transient Tachypnea with Electrocardiogram and Machine Learning

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Highlights

What are the main findings?

- The electrocardiogram parameters and machine learning models, especially the Random Forest classifier, have shown high potential in the early diagnosis of neonatal transient tachypnea.
- The Random Forest model exhibited the best performance compared to other models in terms of F1 score, Matthews Correlation Coefficient, and Area Under the Curve values.

What are the implications of the main findings?

- ECG-based machine learning models can facilitate rapid, accurate, and non-invasive diagnosis of TTN, thereby reducing unnecessary interventions and expediting treatment initiation.
- The Random Forest model presents a promising approach for the development of ECG-based diagnostic systems in pediatric populations and merits further investigation in future studies.

Abstract

Objective: This study explores the utility of electrocardiogram parameters in conjunction with machine learning models for the early diagnosis of neonatal transient tachypnea (TTN). TTN is a common cause of respiratory distress in neonatal intensive care units, and early diagnosis has the potential to reduce invasive interventions and shorten hospital stays. **Methods**: The study retrospectively examined data from 101 neonates diagnosed with TTN and 82 healthy neonates, utilizing parameters such as P, QRS, T angles, and frontal QRS-T angle obtained from ECG. **Results**: Decision Tree, Neural Network, Random Forest, Boosting, and Support Vector Machine models were utilized among the machine learning algorithms. The dataset was split into 65% for training, 20% for validation, and 15% for testing. According to the findings, the Random Forest classification model demonstrated superior performance compared to other models, achieving 71.4% test accuracy, an average AUC value of 0.790, and a Matthews Correlation Coefficient of 0.443. The MCC value indicated that the Random Forest model possesses reliable predictive power even with imbalanced datasets. Notably, ECG parameters such as PR interval, V2 T voltage, and SV1 voltage were identified as the most significant features influencing the model's predictive performance. **Conclusions**: These findings suggest that ECG-based machine learning models can enhance clinical decision-making by facilitating non-invasive, rapid, and accurate diagnosis of TTN. Such artificial intelligence-driven systems hold the potential to mitigate unnecessary interventions, expedite treatment initiation, and improve neonatal prognoses. Future efforts should focus on enhancing model interpretability

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through the incorporation of explainable AI methodologies to facilitate their seamless integration into clinical practice.

Keywords: electrocardiogram; machine learning; neonate transient tachypnea; random forest model; QRS angle; T angle; frontal QRS-T angle

1. Introduction

Transient tachypnea of the newborn (TTN) is a common respiratory condition in newborns that usually resolves spontaneously within 72 hours. While most cases require conservative management, some infants with TTN may develop respiratory distress requiring respiratory support [1]. The goal of respiratory support for TTN is to improve oxygenation and reduce the work of breathing by minimizing lung injury. Initial support typically involves supplemental oxygen delivered via nasal cannula or mask. If respiratory distress persists or worsens, noninvasive ventilation techniques such as continuous positive airway pressure or nasal intermittent positive pressure ventilation may be used [1]. In severe cases where noninvasive methods are insufficient, intubation and mechanical ventilation may be necessary [2]. Studies have shown that a significant proportion of infants with transient tachypnea of the newborn are treated in neonatal intensive care units, and some of these patients require mechanical ventilation support [2]. Ventilator settings are adjusted to provide adequate oxygenation and ventilation while minimizing barotrauma. Lung-protective strategies, such as low tidal volumes and permissive hypercapnia, are important to prevent ventilator-induced lung injury [2]. Furthermore, early and comprehensive clinical evaluation for infants with TTN crucially informs the determination of respiratory support requirements. TTN shows a variable clinical course, with some infants recovering with mild symptoms, while others require more intensive support. This variability means that a single treatment protocol is not suitable for all infants [2].

The QRS-T angle serves as an indicator of ventricular repolarization in ECG evaluation and reflects the angular difference between the mean electrical axes of the QRS complex and the T wave on the ECG [3]. This angle is being investigated as a potential biomarker in the diagnosis and prognostic evaluation of various cardiac pathologies such as myocardial ischemia, arrhythmia, and heart failure [4–6]. Understanding the physiological reference ranges of this angle in neonates and its potential changes in respiratory distress conditions like TTN is crucial for understanding the interaction between cardiac physiology and the respiratory system. In this context, the role of electrocardiographic parameters such as the QRS-T angle and frontal QRS-T angle in the early diagnosis and prediction of the clinical course of neonatal transient tachypnea warrants thorough investigation [7]. The relationship of these parameters with cardiopulmonary adaptation mechanisms in neonates and their potential clinical value, especially in patients requiring non-invasive ventilation, requires further elucidation [1]. Furthermore, clarifying the extent to which these electrocardiographic findings reflect the intricate physiological interactions between the heart and lungs, and their contribution to the pathophysiology of neonatal respiratory distress syndromes, is essential. The potential utility of these parameters as a biomarker for the early diagnosis of neonatal transient tachypnea, a frequent cause for admission to neonatal intensive care units, and for assessing the risk of complications, holds significant importance due to its potential to predict the necessity for invasive and non-invasive respiratory support.

Analysis of electrocardiogram findings with machine learning algorithms, extending beyond traditional parameters such as the QRS-T angle, offers novel avenues for the early diagnosis and prognosis of neonatal transient tachypnea by identifying complex patterns and subtle underlying physiological alterations. Machine learning methodologies are increasingly utilized and continuously evolving, offering significant advancements in diagnostic and monitoring workflows. In this context, the performance of algorithms such as Decision Tree, Random Forest, Boosting, Neural Network, and Support Vector Machine, when applied to ECG data for the diagnosis and

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prognosis of TTN, warrants detailed examination. Specifically, combining these algorithms with distinct electrocardiographic parameters, such as P, QRS, T angles, and the frontal QRS-T angle, can enhance predictive power in the early diagnosis of neonatal transient tachypnea and in determining the risk of complications [8,9]. These advanced analytical methods demonstrate that the QRS-T angle serves as an indicator reflecting heterogeneity in ventricular repolarization [8] and is also associated with critical outcomes such as sudden cardiac death [3]. Such assessment can enable a deeper understanding of neonatal cardiac adaptation processes. Through these algorithms, the potential for early diagnosis of transient tachypnea in newborns can be enhanced, thereby allowing for more expedited determination of appropriate treatment strategies [10]. The role of machine learning in elucidating neonatal cardiopulmonary adaptation mechanisms holds significant promise, particularly in clarifying the pathophysiology of TTN and addressing existing knowledge gaps in this domain [11]. Given the demonstrated success of machine learning algorithms in the early diagnosis and management of other critical neonatal conditions, including sepsis [10], heart murmurs [12], and bronchopulmonary dysplasia in neonatal intensive care units, similar potential is anticipated for TTN. These techniques can improve neonatal outcomes by enhancing diagnostic accuracy and timeliness, and by guiding individualized treatment approaches [12].

This study aims to evaluate the potential for early diagnosis of transient tachypnea in neonates admitted to the neonatal intensive care unit by integrating electrocardiogram parameters, specifically P, QRS, T angles, and frontal QRS-T angle, with machine learning algorithms. This approach seeks to facilitate the rapid and accurate non-invasive diagnosis of TTN, thereby reducing unnecessary interventions and enabling earlier initiation of treatment. This approach can shorten hospitalization durations related to TTN in neonatal intensive care units and decrease complication rates [9,10]. Furthermore, the analysis of ECG-based physiological signals through machine learning can not only enhance diagnostic accuracy but also elucidate the underlying pathophysiological mechanisms of TTN [13]. Especially in resource-limited settings, this can contribute to the overall improvement of neonatal health by reducing dependence on expensive and invasive diagnostic methods. Thus, it will lay a foundation for future research by overcoming current challenges in the clinical application of ML for the early detection and management of critical conditions in the neonatal period.

2. Methodology

2.1. Data Collection

This retrospective study was conducted by including 101 neonatal patients diagnosed with neonatal transient tachypnea at Izmir Buca Seyfi Demirsoy Training and Research Hospital between June and December 2024, alongside a healthy control group of 82 neonates. Demographic data, blood tests taken at admission, respiratory support received, 12-lead electrocardiograms recorded within the first 2-6 hours of birth, and transthoracic echocardiography (Philips Ultrasound Inc./USA) data evaluated within the first 48 hours were included in the study. All ECGs included in the study were retrospectively recorded from files and obtained in accordance with standard neonatology protocols, with a paper speed of 25 mm/sec and a sensitivity of 10 mm/mV. Subsequently, each ECG record was manually reviewed by an experienced pediatric cardiologist to confirm the accuracy of measurements and the absence of artifacts. The sum of V1 S-wave voltage and V6 R-wave voltage was calculated as a total for ventricular hypertrophy [14,15]. The calculation of P, QRS, and T wave angles from each ECG was performed by manually determining the frontal vectors representing the spatial orientation of each wave. QRS-T angles were calculated using the Frontal QRS-T angle method, which involves determining the mean electrical axes of the QRS complex and the T wave and then calculating the angle between these two vectors [3]. From the calculated ECG data, parameters such as heart rate, PR interval, QRS duration, RR interval, QT interval, cQT, V1 S-wave voltage, V6 R-wave voltage, and P, QRS, T angles, and frontal QRS-T angle were calculated and noted. Patients whose neonatal transient tachypnea was consistent with the Turkish Neonatology

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Society's "Respiratory Distress in Term Neonates Diagnosis, Treatment, and Prevention Guide" were included in the study [16].

Patients with arrhythmias on ECG and those with congenital heart disease (excluding Patent Ductus Arteriosus and Patent Foramen Ovale) on echo were excluded from the study. Additionally, other conditions that could mimic TTN symptoms, such as metabolic diseases, severe infections, or neurological disorders, were taken as exclusion criteria [16]. These exclusion criteria were meticulously applied to ensure that the study results more accurately reflected the physiological processes specific to TTN. This approach aimed to create a homogeneous study group to examine the pure clinical and electrophysiological profile of TTN.

Our study was approved by the Izmir Buca Seyfi Demirsoy Teaching and Research Hospital Ethics Committee (ethical decision number 2025/388, dated 29.01.2025) and conducted in accordance with the principles of the Declaration of Helsinki

2.2. Statistical Analysis and Machine Learning

Statistical analyses and machine learning methodologies were employed to assess the data using the open-source JASP 0.95.2 software [17]. Continuous variables were reported as mean ± standard deviation for parametric distributions and as medians for non-parametric distributions; categorical variables were presented as counts and percentages. The Kolmogorov–Smirnov test was performed to ascertain the normality of data distribution. Bivariate relationships between variables were assessed using a simple correlation test. Differences among categorical variables were investigated through chi-square analysis. For quantitative comparisons, Student's t-test and ANOVA were utilized for normally distributed parameters, while the Mann Whitney U and Kruskal Wallis tests were applied for parameters demonstrating non-normal distribution. A p-value of <0.05 was designated as statistically significant for all analyses. The Random Forest algorithm, located under the classification section of the machine learning tab in the JASP program, will be employed for machine learning. JASP is an open-source project with structural support from the University of Amsterdam and others. The dataset will be allocated as follows: 65% for the training set, 20% for the validation set, and 15% for the test set. Key metrics to be recorded include Support, Accuracy, Precision, Recall, False Positive Rate, False Discovery Rate, F1 Score, Matthews Correlation Coefficient, Area Under Curve, Negative Predictive Value, True Negative Rate, and False Negative Rate. Furthermore, for the machine learning model, Mean Decrease in Accuracy, Total increase in Node Purity, and Mean dropout loss values of the features will be documented. This study designates the hemodynamically significant hPDA group and the hemodynamically insignificant, spontaneously resolving aPDA group as the target variables.

3. Results

3.1. Statistical Results

A total of 183 cases were included in the study (CG: n=82, PG: n=101). Of these patients, 42 in the CG and 59 in the PG were female(p:0.33). The median birth weight of the CG was 3280 g, while that of the PG was 3020 g, and this difference was statistically significant (p=0.010). Similarly, median body surface area values were found to be higher in the CG (CG: 6.74, PG: 6.47), and the difference was significant(p:0.02). When body surface area was examined, the median for CG was 6.74, and for PG it was 6.47(p:0.07). The median gestational age for CG was 39, and for PG it was 38 (p:0.06; Table 1).

In addition, for the patient group only: the median duration of ventilation was 2 days, with a minimum of 1 day and a maximum of 7 days. The maximum intubation period was recorded as 6 days. The median length of stay was observed to be 5 days (min:3 day, max; 35 day).

In the ECG data; HR values for CG median was 137, and for PG median was 136. PR interval values for CG median was 102 milliseconds, and for PG median was 108 ms(p:0.1). QRS values for CG median was 66 ms; for PG median was 67 ms(p:0.86). QT values for CG median was 289 ms; for

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PG median was 302 ms(p:0.02). RR interval median values were similar for both groups (p:0.337). QTC values for CG median was 437 ms; for PG median was 447 ms. Tp-e values for CG: median QTC values for CG median was 437 ms; for PG median was 447 ms(p;0.37). Tp-e values for CG: median 50 ms; PG: median 60 ms(p:0.111). Tp-e/QT ratios for CG median was 178 ms, for PG median 196 ms. Tp-e/QTc ratios for CG median was 117 ms; for PG median 134 ms(p:0.136).

ECG voltage values were also recorded. RV5 voltage values were recorded as a median of 0.7 mVolt(mV) for CG and 0.8 mV for PG (p:0.387). SV1 voltage values were a median of 0.3 mV for CG and 0.2 mV for PG (p:0.002. V2 T voltage values were found to be a median of 1.0 for CG and 0.7 mV for PG (p:0.06). RV5+SV1 voltage values were found to be a median of 1.2 for CG and 1.1 for PG (p:0.290).

Regarding the vectorial values observed in the ECG, the median P-wave angle was recorded as 48° for the Control Group and 51° for the Patient Group (p=0.910). The median QRS-wave angle values were 128° for CG and 131° for PG (p=0.475). The median T-wave angle values were 57° for CG and 53° for PG (p=0.383). The frontal QRS-T angle values were determined to be a median of 62° for CG and 78° for PG (p=0.045)

Regarding the echocardiographic measurements, the median Left Ventricular Ejection Fraction values were determined to be 69% for the Control Group and 65% for the Patient Group (p<0.001). Left Ventricular Posterior Wall Diastole values were a median of 1.6 mm for CG and 2.3 mm for PG (p<0.001). Left Ventricular Internal Dimension Diastole values were 14.9 mm for CG and 14.9 for PG (p=0.768). Interventricular Septum Diastole values were a median of 2.4 mm for CG and 2.8 mm for PG (p<0.001). Right Ventricular Internal Dimension Diastole values were 13.6 mm for CG and 12.4 mm for PG (p<0.001). Aortic values were a median of 6.8 mm for CG and 6.5 mm for PG (p=0.09). Left Atrial Diameter values were a median of 9.2 mm for CG and 8.7 mm for PG. Left Ventricular Mass values were a median of 3.548 for CG and 4.624 for PG (p<0.001). Left Ventricular Mass Index values were a median of 0.531 for CG and 0.714 for PG (p<0.001; Table 1).

Table 1. Descriptive Statistics.

		Median	Quartile1	Quartile 3	P value
Weigt(gr)	CG	3280	2966	3575	**0.01**
	PG	3020	2610	3445	
Weight percentil	CG	34	18	67	0.305
	PG	39	18	54	
Body Mass İndex	CG	6.74	6.363	7.054	**0.02**
	PG	6.47	5.980	6.917	
Gestation week	CG	39	38	40	0.06
	PG	38	37	39	
Heart Rate	CG	137	124	158	0.1
	PG	136	126	145	
PR interval(ms)	CG	102	90	120	0.057
	PG	108	98	123	
QRS complex(ms)	CG	66	59	89	0.086
	PG	67	57	76	
QT interval(ms)	CG	289	273	309	**0.002**
	PG	302	286	328	

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R-R interval(ms)	CG	450	392	500	0.337
	PG	450	420	480	
corrected QT	CG	437	417	464	0.037
	PG	447	426	471	
Tp-e(ms)	CG	50	40	60	**0.003**
	PG	60	50	80	
Tp-e/QT	CG	0.178	0.143	0.211	0.111
	PG	0.196	0.137	0.259	
Tp-e/QTc	CG	0.117	0.094	0.145	0.136
	PG	0.134	0.091	0.175	
V6 R wave voltage(mV)	CG	0.7	0.5	1.0	0.387
	PG	0.8	0.5	1.2	
V1 S wave voltage(mV)	CG	0.3	0.1	0.7	**0.002**
	PG	0.2	0.0	0.4	
V2 T voltage(mV)	CG	1.0	0.6	1.3	**0.006**
	PG	0.7	0.4	1.1	
Sum of V6 R and V1 waves voltage(mV)	CG	1.2	0.8	1.6	0.290
	PG	1.1	0.7	1.5	
P angle	CG	48	17	67	0.910
	PG	51	24	64	
QRS angle	CG	128	109	160	0.475
	PG	131	111	170	
T angle	CG	57	33	98	0.383
	PG	53	40	73	
Frontal QRS-T angle	CG	62	26	97	**0.045**
	PG	78	46	109	
LV EF (%)	CG	69	65	70	**<0.001**
	PG	65	63	69	
LVPWd(mm)	CG	1.6	1.4	1.96	**<0.001**
	PG	2.3	1.8	2.65	
LVIDd	CG	14.9	13.9	16.05	0.768
	PG	14.9	13.6	16.26	
IVSd	CG	2.4	2.0	2.7	**< 0.001**
	PG	2.8	2.3	3.3	
RVIDd	CG	12.4	11.2	13.46	**< 0.001**
	PG	13.6	12.4	15.23	
LVIDs	CG	9.7	9.2	10.41	0.479

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RVIDs	PG	9.9	9.1	10.95	
	CG	10.2	8.8	11.48	**0.007**
	PG	11.0	9.6	12.20	
Ao diameter	CG	6.8	6.2	7.5	0.009
	PG	6.5	5.9	7.0	
Left Atrial diameter	CG	9.2	8.3	10.3	0.057
	PG	8.7	7.7	9.6	
LV Mass	CG	3.548	2.985	4.152	**< .001**
	PG	4.624	3.778	5.584	
LV Mass index	CG	0.531	0.454	0.603	**< .001**
	PG	0.714	0.605	0.901	

3.2. Machine Learning Results

In machine learning, Decision Tree Classification (DTC), Neural Network Classification(NNC), Random Forest Classification (RFC), Boosting Classification (BC), and Support Vector Machine Classification(SVMC) models were employed. The dataset, comprising a total of 178 samples, was partitioned into 121 samples for training (65%), 22 samples for validation (15%), and 35 samples for testing (20%).

Decision Tree Classification Model Findings: The Decision Tree Classification model was constructed with 60 splits, exhibiting a complexity penalty of 0.060. The model's validation accuracy was recorded as 0.591, and its test accuracy as 0.600 (Table 2). According to the confusion matrix, 4 of the 14 observed cases from the control group were correctly classified as control, while 10 were erroneously predicted as patient group. Conversely, among the 21 observed cases from the patient group, 4 were incorrectly classified as control, while 17 were correctly predicted as patient group (Table 3). Detailed evaluation of the model performance metrics revealed an overall accuracy of 0.600. For the control group, precision was 0.500 and recall was 0.286, whereas for the patient group, precision was 0.630 and recall was 0.810. The F1-score was calculated as 0.364 for the control group and 0.708 for the patient group. The Area Under the Curve value stood at 0.548 for both groups. The Matthews Correlation Coefficient was determined to be 0.111. Analyzing the feature importance rankings, the variables contributing most significantly to the model's predictive performance were, in descending order: T angle (relative importance 16.845), Frontal QRS-T angle (relative importance 15.990), QRS complex (relative importance 12.673), and V1 S wave voltage (relative importance 8.345). Other variables, such as the V6 R wave voltage, exhibited lower relative importance. Average dropout loss values further illustrate the interactions of these variables within the model.

Neural Network Classification Model Findings: The model was constructed using 20 nodes with 2 hidden layer. Its validation accuracy was recorded as 0.545, and its test accuracy as 0.600 (Table 2). Confusion matrix analysis revealed that out of 15 observed cases from the control group, 1 were correctly classified, while 14 were erroneously predicted as the patient group. Conversely, among the 20 observed cases from the patient group, 20 were correctly classified, while 0 were mistakenly predicted as the control group (Table 3). The overall accuracy of the model was calculated as 0.600. For the control group, precision was 1.000 and recall was 0.67, while for the patient group, precision was 0.588 and recall was 1.000. The F1-score was determined to be 0.125 for the control group and 0.741 for the patient group. The Area Under the Curve value was 0.500 for the control group and 0.500 for the patient group. The Matthews Correlation Coefficient was found to be 0.198. In this model, feature importance metrics indicated a balanced data distribution, yielding comparable mean dropout loss values.

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Random Forest Classification Model Findings: This model was constructed using 69 trees and 3 features at each split. The model's validation accuracy was recorded as 0.455, and its test accuracy as 0.800(Table 2). According to the confusion matrix analysis, 10 of the 12 observed cases from the control group were correctly classified as control, while 2 were erroneously predicted as the patient group. Conversely, among the 23 observed cases from the patient group, 5 were incorrectly classified as control, while 18 were correctly predicted as the patient group (Table 3). These results indicate that the model identified the patient group with a higher success rate compared to the control group. A detailed evaluation of the model performance metrics revealed an overall accuracy of 0.800. For the control group, precision was 0.667 and recall was 0.833. whereas for the patient group, precision was 0.900 and recall was 0.783. This indicates a higher success rate in detecting the patient group. The F1-score was calculated as 0.741 for the control group and 0.837 for the patient group. The Area Under the Curve values were 0.701 for the control group and 0.761 for the patient group, with an average AUC value of 0.731. The Matthews Correlation Coefficient was determined to be 0.591. Based on the feature importance ranking, the variables contributing most significantly to the model's predictive performance were, in descending order: Heart Rate (0.024), Sum of V6 R and V1 S waves voltage (0.006), and QRS complex (0.004).

Boosting Classification Model Findings: The model was constructed using 4 trees. A shrinkage value of 0.1 suggests that the model is prone to overfitting. The model's validation accuracy was recorded as 0.545, and its test accuracy as 0.600 (Table 2). According to the confusion matrix analysis, 12 of the 19 observed cases from the control group were correctly classified as control, while 7 were erroneously predicted as the patient group. Conversely, among the 16 observed cases from the patient group, 7 were incorrectly classified as control, while 9 were correctly predicted as the patient group (Table 3). A detailed evaluation of the model performance metrics revealed an overall accuracy of 0.600. For the control group, precision was 0.632 and recall was 0.632, whereas for the patient group, precision was 0.563 and recall was 0.563. This indicates a higher success rate in detecting the patient group. The F1-score was calculated as 0.632 for the control group and 0.563 for the patient group. The Area Under the Curve values were 0.668 (control group) and 0.461 (patient group), with an average AUC value of 0.564. The Matthews Correlation Coefficient was determined to be 0.194. Based on the feature importance ranking, the variables contributing most significantly to the model's predictive performance were, in descending order: Frontal QRS-T angle (28.971), V1 S wave voltage (26.655), cQT (24.391), and PR interval (19.983).

Support Vector Machine Classification Model Findings: The developed Support Vector Machine model was configured with a violation cost of 0.010 and comprises 107 support vectors. The model's validation accuracy was recorded as 0.682, and its test accuracy as 0.629 (Table 2). According to the confusion matrix, 2 cases from the control group were correctly classified as CG, while 13 cases were erroneously predicted as the Patient Group. Conversely, among the patient group, 20 cases were correctly classified as the Patient Group, while 0 cases were mistakenly assigned to the Control Group (Table 3). The model's overall accuracy was determined to be 0.629. While the model exhibited higher recall 1.000 and F1-score (0.755) for the detection of the patient group, the recall (0.133) and F1-score (0.235) were lower for the control group. The model's Matthews Correlation Coefficient was 0.284 indicating a classification performance slightly better than random chance but not a strong correlation. The Area Under the Curve value was calculated as 0.567 for both groups, suggesting a moderate discriminative ability for the model. An examination of the mean dropout loss values, which reflect each feature's contribution to the model's predictive performance, revealed that electrocardiographic parameters such as ECG heart rate (0.429), SV1 voltage (0.420), QRS (0.419), Forntal QRS-T angle (0.419), QT interval (0.419) and cQT (0.418) were the most significant contributors to the SVM model's predictive performance. In contrast, the effects of features like P-angle (0.402), RR interval (0.407) and QRS angle (0.409) were more limited.

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Table 2. Summaries of Models.

Models	*Model Summaries*						
Decision Tree Classification	**Complexity penalty**	**Splits**	**n(Train)**	**n(Validation)**	**n(Test)**	**Validation Accuracy**	**Test Accuracy**
	0.000	60	121	22	35	0.591	0.600
Neural Network Classification	**Hidden Layers**	**Nodes**	**n(Train)**	**n(Validation)**	**n(Test)**	**Validation Accuracy**	**Test Accuracy**
	2	20	121	22	35	0.545	0.600
Random Forest Classification	**Trees**	**Features per split**	**n(Train)**	**n(Validation)**	**n(Test)**	**Validation Accuracy**	**Test Accuracy**
	69	3	121	22	35	0.455	0.800
Boosting Classification	**Trees**	**Shrinkage**	**n(Train)**	**n(Validation)**	**n(Test)**	**Validation Accuracy**	**Test Accuracy**
	4	0.100	121	22	35	0.545	0.600
Support Vector Machine Classification	**Violation cost**	**Support Vectors**	**n(Train)**	**n(Validation)**	**n(Test)**	**Validation Accuracy**	**Test Accuracy**
	0.010	107	121	22	35	0.682	0.629

Table 3. Confusion Matrix.

			Predicted	
			Control Group	**Patient Group**
Decision Tree Classification	Observed	Control Group	4	10
		Patient Group	4	17
Neural Network Classification	Observed	Control Group	1	14
		Patient Group	0	20
Random Forest Classification	Observed	Control Group	10	2
		Patient Group	5	18
Boosting Classification	Observed	Control Group	12	7
		Patient Group	7	9
Support Vector Machine Classification	Observed	Control Group	2	13
		Patient Group	0	20

4. Discussion

In this study, the potential of electrocardiogram parameters and machine learning models in the early diagnosis of transient tachypnea of the newborn was evaluated. Firstly, when we evaluated the

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classical statistical results, there are a limited number of studies on the use of electrocardiogram data, especially QRS-T angles, in the early diagnosis of transient tachypnea of the newborn. This increases the originality of the study and its potential importance in clinical practice. Existing literature reports that electrocardiogram-based deep learning models show high performance in predicting various cardiac abnormalities such as ASD detection and heart failure in the pediatric population [18,19]. Since the QRS-T angle is globally considered as the combination of ventricular depolarization and repolarization processes, this parameter is important for its potential to reflect changes in ventricular function in transient tachypnea of the newborn [14]. In this context, the analysis of ECG-based QRS-T angles will stand out as a valuable indicator for detecting electrical changes in ventricular pathophysiology that cannot be detected echocardiographically in transient tachypnea of the newborn. These angles, especially as a combination of ventricular depolarization and repolarization processes, can offer a deeper understanding compared to traditional methods in the early and accurate diagnosis of transient tachypnea of the newborn and will make significant contributions to clinical decision-making processes.

In our study, based on classical statistical results, the QRS-T Axis was found to be 128 degrees in the control group and 131 degrees in the patient group. These values are similar to those reported in [20]. We believe that the significant outcome of this angle evaluation in our study may be related to the volume and pressure load on the right ventricle. Indeed, transient tachypnea of the newborn is a condition resulting from insufficient clearance of fetal lung fluid, which can lead to an increase in pulmonary vascular resistance and, consequently, an increased load on the right ventricle [16]. This pathophysiological change can correlate with the variations observed in the QRS-T angle and electrographically reflect early deteriorations in right ventricular functions [14]. This situation enhances the diagnostic value of QRS-T angles in assessing the heart's structural and functional adaptations during the neonatal period [18,21]. This suggests that electrocardiographic findings, particularly changes in the QRS-T angle, can be considered an important indicator of right ventricular volume and pressure overload in the early stages of transient tachypnea of the newborn [22].

Our study's main focus also reveals that machine learning algorithms, by analyzing complex patterns in ECG data, offer a higher diagnostic accuracy potential compared to traditional methods. According to classical statistical results, ECG data, especially the QRS-T angle, yielded a borderline p-value, whereas these values were utilized more efficiently in the results of machine learning models. Among the models, the Random Forest classification demonstrated the best performance. It outperformed other models, especially in terms of F1 score, MCC, and AUC values. The F1 score is a critical metric used to evaluate the performance of machine learning models, particularly reflecting the balance between precision and recall in classification problems. This score is a harmonic mean that summarizes the model's ability to accurately predict the positive class, considering both the accuracy of positive predictions and how many of all true positives are captured [10,23]. Random Forest models generate robust and stable predictions that compensate for the weaknesses of individual trees by building multiple decision trees on random feature subsets and data samples [24]. This ensemble approach reduces overfitting and increases the model's generalization ability, leading to more robust performance on unseen data [9]. Recent articles indicate that studies using Random Forest models have started to show better performance compared to other models [25–27]. In this respect, our study provided values close to those in the literature. Our study has shown that Random Forest can be widely used and yield successful results, especially in the development of ECG-based diagnostic systems in pediatric populations. More emphasis should be placed on this model in future studies.

In machine learning, we observe that the models making the weakest predictions are NC, with a Control group F1 score of 0.125. Following this, the SVMC model showed a CG F1 score of 0.235, and the DTC model exhibited a CG F1 score of 0.364. In contrast, Boosting models, especially algorithms like XGBoost, are considered capable of providing stronger predictions due to their ability to sequentially combine weak learners to improve the overall performance of the model [13]. Indeed, XGBoost can demonstrate superior performance in complex datasets with high accuracy and

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precision by using boosted tree models [9]. In the standalone xBC model, the CG F1 score was determined as 0.632, and the patient F1 score as 0.563; however, when compared to the Random Forest model, which showed the best performance, XGBoost was observed to lag behind in certain situations, particularly in terms of F1 score [28,29]. Correspondingly, as seen in our study, Random Forest models are reported to achieve higher accuracy rates in the diagnosis of complex pediatric cardiac diseases [9]. This situation has shown that Random Forest can be widely used and yield successful results, especially in the development of ECG-based diagnostic systems in pediatric populations [30,31]. Therefore, it is important to further investigate the potential of Random Forest in future research and ensure its integration into clinical applications. Furthermore, the use of explainable artificial intelligence methods, such as SHAP values, to increase the interpretability of the Random Forest model and facilitate its integration into clinical decision support systems, can more clearly reveal the contribution of each ECG parameter to the diagnosis [32].

When evaluating machine learning models, it is necessary to look at the Matthews Correlation Coefficient values after the F1 score. From this perspective, MCC is a comprehensive and reliable performance metric, especially used in binary classification problems. MCC measures a model's ability to correctly predict both positive and negative data samples, regardless of class imbalances in the dataset. The MCC value ranges from -1 to +1, with +1 indicating perfect prediction power, 0 indicating random prediction, and -1 indicating a completely inverse prediction [33,34]. In our study, the MCC value of the Random Forest model was found to be higher compared to other models, demonstrating reliable performance even with imbalanced datasets and high predictive power in diagnosing transient tachypnea of the newborn. This MCC finding emphasizes that Random Forest can be widely used and yield successful results, especially in the development of ECG-based diagnostic systems in pediatric populations. This situation shows that Random Forest can successfully capture complex and non-linear relationships present in ECG data, thereby detecting subtle distinctions that other classifiers cannot overcome [9,27]. In this context, it can be said that Random Forest is a promising approach for the development of artificial intelligence-supported ECG interpretation systems, especially in pediatric cardiology [35].

In the future, machine learning and its sub-models will be featured in more research. Especially in the clinical follow-up of critically ill and hospitalized patients, it is of great importance to generate data through such pioneering studies regarding deterioration, complications, and mortality. The collection and analysis of this data will pave the way for the development of artificial intelligence-supported decision-making systems, marking a critical step in improving survival and long-term prognosis in neonatal intensive care units. In this context, machine learning models, especially using biomarkers such as ECG parameters and P, QRS, and T angles, can significantly accelerate the early diagnosis of conditions like transient tachypnea of the newborn. Furthermore, integrating transparent artificial intelligence approaches is crucial to increase the interpretability of these models and build trust among clinicians. This facilitates understanding the features underlying model predictions, helping clinicians make more informed diagnostic and treatment decisions. Therefore, integrating explainable artificial intelligence techniques into ECG-based machine learning models will both increase clinical acceptability and minimize the risk of medical errors. Such integrated systems offer opportunities for proactive intervention by pre-identifying potential risks, especially for conditions requiring continuous monitoring in neonatal intensive care units [36]. Additionally, combining AI techniques with data obtained from wearable sensors can improve the quality of signals, which are more prone to noise like motion artifacts, thereby enabling more accurate diagnosis and monitoring [12]. This indicates that the performance of models can be further improved by using data obtained not only from ECG but also from other physiological signals such as photoplethysmography [37]. These developments also form the basis for applications such as predicting readiness for extubation [10] or detecting apnea [12] through automated analysis of cardiorespiratory behaviors in newborns.

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5. Conclusions

This study evaluated the potential of machine learning models with electrocardiogram parameters in the early diagnosis of transient tachypnea of the newborn. The relationship of electrocardiographic findings such as P, QRS, T angles, and frontal QRS-T angle with cardiopulmonary adaptation mechanisms in newborns and their potential clinical value were emphasized. Various machine learning algorithms, including Random Forest, Decision Tree, Neural Network, Boosting, and Support Vector Machine, were used in the study, and the Random Forest model was found to exhibit the best performance in terms of F1 score, Matthews Correlation Coefficient, and Area Under the Curve values. The MCC value, in particular, demonstrated reliable performance even with imbalanced datasets and highlighted the model's predictive power, indicating that Random Forest has high potential in the diagnosis of TTN. These findings suggest that ECG-based machine learning models can enable rapid and accurate non-invasive diagnosis of transient tachypnea of the newborn, thereby reducing unnecessary interventions and providing an opportunity for earlier treatment. It was concluded that the integration of artificial intelligence-supported decision support systems into neonatology will be a critical step in improving survival and long-term prognosis in neonatal intensive care units.

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Informed Consent Statement: Patient consent was waived due to the retrospective design of this study.

Data Availability Statement: Data is publicly unavailable due to privacy/ethical restrictions but may be supplied upon reasonable demand for academic research.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

TTN: Transient Tachypnea of Newborn
ECG Electrocardiogram
ML: Machine Learning
DTC: Decision Tree Classification
NNC: Neural Network Classification
RFC: Random Forest Classification
BC: Boosting Classification
SVMC: Support Vector Machine Classification

References

1. Zhang, H.; Zuo, Y.; Li, Q.; Sun, J.; Li, G.; Wang, Q. Efficacy and Predictors of Noninvasive Ventilation in Neonates with Congenital Heart Disease. **2024**. https://doi.org/10.21203/rs.3.rs-4699277/v1.

 doi:10.20944/preprints202512.0061.v2

2. Bruschettini, M.; Hassan, K.-O.; Romantsik, O.; Banzi, R.; Calevo, M. G.; Moresco, L. Interventions for the Management of Transient Tachypnoea of the Newborn - an Overview of Systematic Reviews. *Cochrane Database of Systematic Reviews* **2022**, *2022* (2). https://doi.org/10.1002/14651858.cd013563.pub2.
3. Oehler, A.; Feldman, T.; Henrikson, C. A.; Tereshchenko, L. G. QRS-T Angle: A Review. *Annals of Noninvasive Electrocardiology* **2014**, *19* (6), 534. https://doi.org/10.1111/anec.12206.
4. Hnatkova, K.; Seegers, J.; Barthel, P.; Novotný, T.; Smetana, P.; Zabel, M.; Schmidt, G.; Malík, M. Clinical Value of Different QRS-T Angle Expressions. *EP Europace* **2017**, *20* (8), 1352. https://doi.org/10.1093/europace/eux246.
5. Zhang, X.; Zhu, Q.; Zhu, L.; Jiang, H.; Xie, J.; Huang, W.; Xu, B. Spatial/Frontal QRS-T Angle Predicts All-Cause Mortality and Cardiac Mortality: A Meta-Analysis. *PLoS ONE* **2015**, *10* (8). https://doi.org/10.1371/journal.pone.0136174.
6. Aro, A. L.; Huikuri, H. V.; Tikkanen, J. T.; Junttila, J.; Rissanen, H.; Reunanen, A.; Anttonen, O. QRS-T Angle as a Predictor of Sudden Cardiac Death in a Middle-Aged General Population. *EP Europace* **2011**, *14* (6), 872. https://doi.org/10.1093/europace/eur393.
7. Ciucurel, C.; Iconaru, E. I. The Relationship between the Frontal QRS-T Angle on ECG and Physical Activity Level in Young Adults. *International Journal of Environmental Research and Public Health* **2023**, *20* (3), 2411. https://doi.org/10.3390/ijerph20032411.
8. Algül, E.; Özbeyaz, N. B.; Şahan, H. F.; Aydınyılmaz, F.; Gezer, E.; Sunman, H.; Çimen, T.; Tulmaç, M. Frontal QRS - T Angle Is Associated with Severity and Prognosis of Acute Pulmonary Embolism. *Journal of Electrocardiology* **2023**, *79*, 8. https://doi.org/10.1016/j.jelectrocard.2023.02.003.
9. Jura, A. M. C.; Popescu, D.-E.; Cîtu, C.; Biriş, M.; Pienar, C.; Paul, C.; Petrescu, O. M.; Constantin, A. T.; Dinulescu, A.; Roşca, I. Predicting Risk for Patent Ductus Arteriosus in the Neonate: A Machine Learning Analysis. *Medicina* **2025**, *61* (4), 603. https://doi.org/10.3390/medicina61040603.
10. Keleş, E.; Bağcı, U. The Past, Current, and Future of Neonatal Intensive Care Units with Artificial Intelligence: A Systematic Review. *npj Digital Medicine* **2023**, *6* (1). https://doi.org/10.1038/s41746-023-00941-5.
11. Amodeo, I.; Nunzio, G. D.; Raffaeli, G.; Borzani, I.; Griggio, A.; Conte, L.; Macchini, F.; Condò, V.; Persico, N.; Fabietti, I.; Ghirardello, S.; Pierro, M.; Tafuri, B.; Como, G.; Cascio, D.; Colnaghi, M.; Mosca, F.; Cavallaro, G. A maChine and Deep Learning Approach to Predict pulmoNary hyperteNsIon in newbornS with Congenital Diaphragmatic Hernia (CLANNISH): Protocol for a Retrospective Study. *PLoS ONE* **2021**, *16* (11). https://doi.org/10.1371/journal.pone.0259724.
12. Sitaula, C.; Grooby, E.; Kwok, T. C.; Sharkey, D.; Marzbanrad, F.; Malhotra, A. K. Artificial Intelligence-Driven Wearable Technologies for Neonatal Cardiorespiratory Monitoring. Part 2: Artificial Intelligence. *Pediatric Research* **2022**, *93* (2), 426. https://doi.org/10.1038/s41390-022-02417-w.
13. Rahman, J. S.; Brankovic, A.; Tracy, M.; Khanna, S. Exploring Computational Techniques in Preprocessing Neonatal Physiological Signals for Detecting Adverse Outcomes: Scoping Review. *Interactive Journal of Medical Research* **2024**, *13*. https://doi.org/10.2196/46946.
14. Molin, J.; Hartmann, J.; Pærregaard, M. M.; Thygesen, C. B.; Sillesen, A.; Raja, A. A.; Vøgg, R. O. B.; Iversen, K.; Bundgaard, H.; Christensen, A. H. The Neonatal QRS Complex and Its Association with Left Ventricular Mass. *Pediatric Cardiology* **2023**, *45* (2), 248. https://doi.org/10.1007/s00246-023-03361-0.
15. Sokolow, M.; Lyon, T. P. The Ventricular Complex in Left Ventricular Hypertrophy as Obtained by Unipolar Precordial and Limb Leads. *American Heart Journal* **1949**, *37* (2), 161. https://doi.org/10.1016/0002-8703(49)90562-1.
16. Özer, E. A.; Demirel, G.; Tüzün, F.; Koç, E.; Vural, M.; Duman, N.; Erdeve, Ö.; Baş, A. Y.; Çetinkaya, M.; Narlı, N. TÜRK NEONATOLOJİ DERNEĞİ TERM YENİDOĞANDA SOLUNUM SIKINTISI TANI, TEDAVİ VE KORUNMA REHBERİ 2021, 2021.
17. JASP Team. {{JASP (Version 0.95.2)[Computer Software]}}. (2025). 2025. https://jasp-stats.org/.
18. Mayourian, J.; Geggel, R. L.; Cava, W. L.; Ghelani, S. J.; Triedman, J. K. Pediatric Electrocardiogram-Based Deep Learning to Predict Secundum Atrial Septal Defects. *Pediatric Cardiology* **2024**. https://doi.org/10.1007/s00246-024-03540-7.

 doi:10.20944/preprints202512.0061.v2

19. Bizopoulos, P.; Koutsouris, D. Deep Learning in Cardiology. *IEEE Reviews in Biomedical Engineering* **2018**, *12*, 168. https://doi.org/10.1109/rbme.2018.2885714.
20. Lue, H.; Wu, M.; Wang, J.; Lin, M.; Lu, C.; Chiu, S.; Chen, C.; Wu, E.; Wang, C.; Fu, C.-M.; Tseng, W.; Chang, W.-H.; Lee, M.-C. Normal ECG Standards and Percentile Charts for Infants, Children and Adolescents. *Pediatrics & Neonatology* **2022**, *64* (3), 256. https://doi.org/10.1016/j.pedneo.2022.07.013.
21. Dehn, A. M.; Pærregaard, M. M.; Sellmer, A.; Dannesbo, S.; Blixenkrone-Møller, E.; Sillesen, A.; Raja, A. A.; Iversen, K.; Bundgaard, H.; Christensen, A. H.; Hjortdal, V. E. Electrocardiographic Characteristics in 438 Neonates with Atrial Septal Defects. *Pediatric Cardiology* **2023**, *45* (3), 580. https://doi.org/10.1007/s00246-023-03324-5.
22. Peña-Juárez, R. A.; García-Canales, A.; Garrido-García, L. M.; Valerio-Carballo, C. A. Situación Del Intervalo QTc En El Período Neonatal En Un Hospital Del Occidente de México, Estudio Piloto. *Archivos de cardiología de México* **2017**, *88* (5), 376. https://doi.org/10.1016/j.acmx.2017.09.006.
23. Chicco, D.; Jurman, G. The Advantages of the Matthews Correlation Coefficient (MCC) over F1 Score and Accuracy in Binary Classification Evaluation. *BMC Genomics* **2020**, *21* (1). https://doi.org/10.1186/s12864-019-6413-7.
24. Doubleday, K.; Zhou, J.; Zhou, H.; Fu, H. Risk Controlled Decision Trees and Random Forests for Precision Medicine. *Statistics in Medicine* **2021**, *41* (4), 719. https://doi.org/10.1002/sim.9253.
25. Wallace, M. L.; Mentch, L.; Wheeler, B. J.; Tapia, A. L.; Richards, M.; Zhou, S.; Yi, L.; Redline, S.; Buysse, D. J. Use and Misuse of Random Forest Variable Importance Metrics in Medicine: Demonstrations through Incident Stroke Prediction. *BMC Medical Research Methodology* **2023**, *23* (1). https://doi.org/10.1186/s12874-023-01965-x.
26. Xu, C.; Wang, J.; Zheng, T.; Cao, Y.; Ye, F. Prediction of Prognosis and Survival of Patients with Gastric Cancer by Weighted Improved Random Forest Model. *Archives of Medical Science* **2021**. https://doi.org/10.5114/aoms/135594.
27. Pal, M.; Parija, S. Prediction of Heart Diseases Using Random Forest. *Journal of Physics Conference Series* **2021**, *1817* (1), 12009. https://doi.org/10.1088/1742-6596/1817/1/012009.
28. Karimi, M.; Nafei, Z.; Shamsi, F.; Akbarian, E. Prediction of COVID-19 Severity and Mortality in Hospitalized Children Using Machine Learning Tree-Based Classifiers. *Research Square (Research Square)* **2024**. https://doi.org/10.21203/rs.3.rs-4926945/v1.
29. Shokouhmand, A.; Aranoff, N. D.; Driggin, E.; Green, P.; Tavassolian, N. Efficient Detection of Aortic Stenosis Using Morphological Characteristics of Cardiomechanical Signals and Heart Rate Variability Parameters. *Scientific Reports* **2021**, *11* (1). https://doi.org/10.1038/s41598-021-03441-2.
30. Sadegh-Zadeh, S.; Khezerlouy-Aghdam, N.; Sakha, H.; Toufan, M.; Behravan, M.; Vahedi, A.; Rahimi, M.; Hosseini, H.; Khanjani, S.; Bayat, B.; Ali, S. A.; Hajizadeh, R.; Eshraghi, A.; Ghidary, S. S.; Saadat, M. Precision Diagnostics in Cardiac Tumours: Integrating Echocardiography and Pathology with Advanced Machine Learning on Limited Data. *Informatics in Medicine Unlocked* **2024**, *49*, 101544. https://doi.org/10.1016/j.imu.2024.101544.
31. Osa-Sanchez, A.; Ramos-Martinez-de-Soria, J.; Zorrilla, A. M.; Ruiz, I. O.; García-Zapirain, B. Wearable Sensors and Artificial Intelligence for Sleep Apnea Detection: A Systematic Review. *Research Square (Research Square)* **2024**. https://doi.org/10.21203/rs.3.rs-5431207/v1.
32. Zheng, W.; Zhu, S.; Wang, X.; Chen, C. M.; Zhang, Z.; Xu, Y.; Mo, X.; Tse, G.; Li, X. Machine Learning for Early Diagnosis of Kawasaki Disease in Acute Febrile Children: Retrospective Cross-Sectional Study in China. *Scientific Reports* **2025**, *15* (1). https://doi.org/10.1038/s41598-025-90919-y.
33. Chicco, D.; Tötsch, N.; Jurman, G. The Matthews Correlation Coefficient (MCC) Is More Reliable than Balanced Accuracy, Bookmaker Informedness, and Markedness in Two-Class Confusion Matrix Evaluation. *BioData Mining* **2021**, *14* (1). https://doi.org/10.1186/s13040-021-00244-z.
34. Chicco, D.; Jurman, G. The Matthews Correlation Coefficient (MCC) Should Replace the ROC AUC as the Standard Metric for Assessing Binary Classification. *BioData Mining* **2023**, *16* (1). https://doi.org/10.1186/s13040-023-00322-4.
35. Leone, D. M.; O'Sullivan, D.; Jaimes, K. B. Artificial Intelligence in Pediatric Electrocardiography: A Comprehensive Review. *Children* **2024**, *12* (1), 25. https://doi.org/10.3390/children12010025.

 doi:10.20944/preprints202512.0061.v2

36. León, C.; Cabon, S.; Patural, H.; Gascoin, G.; Flamant, C.; Roué, J.; Favrais, G.; Beuchée, A.; Pladys, P.; Carrault, G. Evaluation of Maturation in Preterm Infants Through an Ensemble Machine Learning Algorithm Using Physiological Signals. *IEEE Journal of Biomedical and Health Informatics* **2021**, *26* (1), 400. https://doi.org/10.1109/jbhi.2021.3093096.
37. Baker, S.; Yogavijayan, T.; Kandasamy, Y. Towards Non-Invasive and Continuous Blood Pressure Monitoring in Neonatal Intensive Care Using Artificial Intelligence: A Narrative Review. *Healthcare* **2023**, *11* (24), 3107. https://doi.org/10.3390/healthcare11243107.