

## Mortality Rate Pre-assessment Based on Trips Score

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### Authors' contributions

This work was carried out in collaboration between all authors. Authors AK and NN conceived the original idea and contributed to designed the study. Author CD managed the analyses of the study. Author MN managed the literature searches. Authors CD and MN wrote the first draft of manuscript. The final manuscript was written by authors AK and NN. All authors read and approved the final manuscript.

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### ABSTRACT

Treatment and care for newborn babies are provided at medical centres by personnel with the required education and experience using special equipment. Similar to the situation in many other countries, centres with such concentrations are rare; such a situation has required transportation of newborn babies from the centres where they are located to specialised centres. The medical centre that will transport the newborn cannot determine which case is a greater emergency (prioritised) without visiting and inspecting each newborn. In this study, prioritisation of transportation to a Level III newborn medical centre that also fulfils its own transportation needs was studied. In this study, using basic information regarding the newborn (not requiring laboratory tests) without visiting the newborn, the transportation priority of the newborn and the mortality rates were predicted using feed-forward artificial neural networks with high reliability. Prior to transportation, the state of newborn babies is determined using TRIPS scoring. In this way, when more than one transport call is received at the same time, prioritisation will be performed considering mortality rates. Detecting newborn patients' medical conditions will also help in planning what type of equipment and transportation vehicles are required.

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## 1. INTRODUCTION

Newborn transport is a key component of neonatal-perinatal care; babies at high risk are frequently transported from one neonatal intensive care unit (NICU) or hospital to another for a variety of reasons [1,2]. During inter-hospital transport, these babies are exposed to an environment outside of the safety of the NICU. Adequate neonatal transport is a key component of care of the sick newborn who requires referral to tertiary care (Level III) centres that provide higher levels of care.

Many hospitals provide facilities for the care of newborns of varying intensity, where the need for transfer is determined by a requirement for support or treatment beyond that available locally. The designations of hospital facilities that take care of newborns are based on the level of complexity of the care provided.

Level I units provide take care for babies who require more care than healthy newborns but are relatively stable.

Level II neonatal units can care for babies who require more advanced support, such as parenteral nutrition and ventilatory support. These units may also look after babies who require short-term intensive care, such as mechanical ventilation. Babies who require longer-term or more elaborate intensive care, for example, extremely preterm infants, are usually transferred to a Level III unit.

Most of the hospitals do not provide Level III care due to economic reasons. In cases where newborns require intensive care, such newborns must be transported from their existing centre to another centre with higher level standards.

Transportation percentage with incubator is between 7.8% to 86.1%, transportation which is accompanied with doctor is between 4.1% to 45.7%, hypothermia percentage of transported infants is 8-43.8%, hypoglycaemia percentage is between 9.7% to 31.3% and hy-poxemia-acidosis percentage is changing between 20% to 80% in our country [3-6].

There are many factors leading to clinical deterioration in newborns submitted to inter-hospitals transport that depend on transport conditions. Conditions associated with transport

can contribute to patient instability: excess noise, vibration, difference in temperature, distance, duration of transport time, and highway conditions. However, the transport team should be prepared to learn to recognise and minimise these conditions [7].

In addition to the transport conditions, the transport crew is another determining factor affecting the health of the newborn. The number of doctors and nurses in the health crew during transportation and its effect on the health of the newborn must be considered. Kumar et al. [8] analysed the importance of the transportation crew and the road in terms of long- and short-distance transportation. Inner-province transportation is categorised as Group 1, and outside-province transportation is categorised as Group 2. The babies were grouped according to gestational weeks, and their conditions were analysed following transportation. The babies who were affected negatively during transportation and remained alive during the following 24 hours were compared in terms of their biochemical features.

Both gestational age and birth weight are particularly influenced by the transportation process. Therefore, Mohamed and Aly [9] considered newborns weighing less than 1500 grams and showed that there are correlations between transportation among centres and the intensity of intraventricular haemorrhages.

Transporting newborns between centres is likely to affect their medical conditions. By grading challenges and analysing the effects of transportation conditions on newborns, many scoring systems have been created to determine mortality rates.

Neonatal illness severity scores, such as the Clinical Risk Index for Babies (CRIB) [10] and the Score for Neonatal Acute Physiology, version II (SNAP-II) [11], are important for risk adjustment and benchmarking outcomes in neonatal intensive care units (NICUs). However, both CRIB and SNAP-II have been criticised because they are derived from measurements taken over a 12-hour period. CRIB is only validated for infants with a birth weight of < 1500 g, and neither SNAP-II nor CRIB are validated for sequential measurements to determine the change in physiological stability over time.

Sutcuoglu et al. [12] suggested the Transport Related Mortality Score (TREMS) system is predicted mortality based on the values of hypoglycaemia, hypoxia, hypercarbia, hypotension, and hypothermia.

Lee et al. [13] developed The Transport Risk Index of Physiologic Stability (TRIPS) scoring system, which involves collecting data before and after transporting the newborn and assessing physiological conditions during newborn transportation.

Fig. 1 shows that the parameters considered in TRIPS are classified into four groups: temperature, respiratory status, systolic blood pressure and response to noxious stimuli. Each group also has its own points. After all of these points are added, the TRIPS score is obtained. In the TRIPS scoring system, which determines mortality, the mortality rate between 1 and 27% is categorised into six groups: 0.01, 0.03, 0.05, 0.15, 0.18 and 0.27. The parameter values that are considered in determining mortality rates are collected at the patient's current location by visiting him/her.

TRIPS Variable	TRIPS Score Points
<b>Temperature (°C)</b>	
<36.1 or >37.6	8
36.1–36.5 or 37.2–37.6	1
36.6–37.1	0
<b>Respiratory status</b>	
Severe (apnea, gasping, intubated)	14
Moderate (respiratory rate >60/min and/or pulse oximetry <85)	5
None (respiratory rate <60/min and pulse oximetry >85)	0
<b>Systolic blood pressure</b>	
<20	26
20–40	16
>40	0
<b>Response to noxious stimuli</b>	
None, seizure, muscle relaxant	17
Lethargic response, no cry	6
Withdraws vigorously, cries	0

**Fig. 1. TRIPS scale (Lucas da Silva et al. [14])**

In this study, the TRIPS scoring system is considered, and prioritisation of transportation in a Level III newborn medical centre that also provides its own transportation needs was studied. The medical centre is also requested for

transportation by more than one medical centre. The medical centre that will transport the newborn cannot determine which case is a greater emergency (high mortality rate) without visiting and inspecting the newborn. In this study, using basic information regarding the newborn (not requiring laboratory tests) without visiting the newborn, the transportation priority of the newborn and the mortality rates after transportation were predicted with high reliability.

## 2. MATERIALS AND METHODS

### 2.1 Patient Population

In this retrospective study, the transportation data of a private hospital between the years of 2011 and 2014 were used. The hospital whose data were used is the only hospital that has a newborn vehicle and is a Level III centre with 55 available beds for patients.

From the hospital, data such as gender, gestation week, transportation day, transportation location (between hospitals within province or between hospitals outside provinces), transportation distance and TRIPS score given to babies by the transportation crew on the location of acceptance after transportation were gathered. Information of transported infants is held in excel and Patient Information Program which is used in hospital. All data has been taken from those databases and modelled in MATLAB software package and all information has been gained from doctors and nurses who are responsible for new-born unit of the hospital and preferred to have at least one year of expertise. These gathered data used in this study are approved by the board of the hospital.

In this study, data for 138 transported patients were considered. Of the patients, 43% were female and 57% were male newborns. The gestation week of our group was between 22 and 40 weeks. The birth weights were between 500 and 4800 g. The transportation distances were in the range of 5 to 250 km of the babies that were included in our study. Since the input of transportation location is categorical (in city and out of city), It has not been reflected to the table. Average of considered inputs according to genders has been analysed and illustrated in Table 1. Also in Table 2, inputs by gender have been tested with independent- t test in SPSS software. Analysis indicates that all of sig (2-tailed) values are greater than 0,05 while

**Table 1. Input analysis based on gender**

Gender	N	Birth weight mean	Gestation week mean	Transportation day	Transportation distance
Female	57	2071.23	32.67	10.68	163.60
Male	81	2041.60	32.88	11.95	169.65

confidence bound is %95. This result show that there is no difference between the averages of input parameters of female and male infants. Hence, all data has been considered holistically. Using patient data and an artificial neural network approach, the mortality scores based on the TRIPS score can be predicted.

**Table 2. Independent t test**

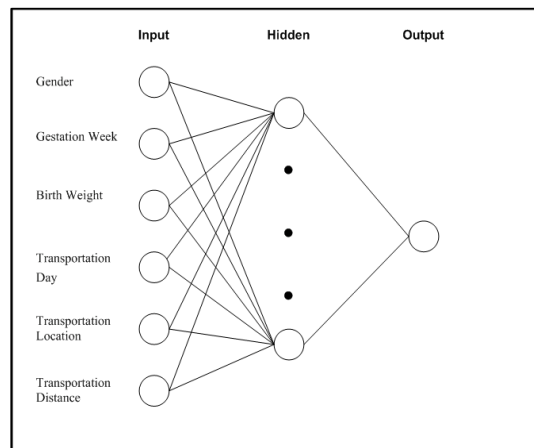
Inputs	Sig (2-tailed)
Gestation Week	0.815
Birth Weight	0.877
Transportation Day	0.688
Transportation Distance	0.583

## 2.2 Artificial Neural Networks

In this study, the states of patients (mortality states) to be transported are aimed to be determined without visiting them using the approach of artificial neural networks. Artificial neural networks (ANNs) are used in a wide variety of areas, particularly for prediction and categorisation. Based on a literature review, although the artificial neural networks approach is not utilised to determine patient scores in the medical sector, it is frequently used in studies of disease diagnosis. Artificial neural networks were used in the work of Kurt et al. [15] in their diagnosis of in their coronary artery, Chowdhury et al. [16] in their diagnosis of neonatal diseases Palaniappan and Awang [17] in their study of determining cardiac diseases and Temurtaş et al. [18] in their diagnosis of diabetes, Karamanli et al. [19] in their diagnosis of obstructive sleep apnea; Santos-Garcia et al. [20] in their morbidity after lung resection, Silva et al. [21] in their mortality assessment in intensive care.

In an ANN, the mathematical relationships between the input and the output are taken into consideration. ANN is divided into two parts: a single perceptron and a multilayer perceptron (MLP). In a single perceptron, input and output are considered, and in a multilayer perceptron (MLP), input, output and at least one hidden layer are included. MLP is flexible in prediction [22]. As a result, an MLP with three layers was used in the present study.

Depending on the training type in an ANN, it is either supervised or unsupervised [23]. For this study, a supervised ANN was chosen. Supervised ANNs hold a number of algorithms. In this study, the feed-forward artificial neural networks approach was used, and Levenberg-Marquardt based on least square error method was preferred as the training algorithm. This is an efficient used algorithm in network trainings [24].



**Fig. 2. Artificial neural network structure**

The data for 138 transport patients were categorised randomly into three groups: learning, validation and test. The data and neuron numbers in each category were determined considering performance values at the end of the artificial neural networks operations. As a performance indicator, the mean square error (MSE) value was used; the MSE formula is given in Equation (1). Data distribution with the lowest MSE value and the lowest number of neurons in the hidden layer was accepted as the ideal solution.

$$MSE = \frac{1}{N} \sum_{i=1}^N (TRIPS_{ANN} - TRIPS_{Actual Value})^2 \quad (1)$$

This study used the Matlab (Neural Network Toolbox) package programme. Six input parameters and one output parameter were considered, and a single hidden layer was used.

In Fig. 2, the input, hidden and output layers are presented.

### 3. RESULTS AND DISCUSSION

TRIPS is a common method used to determine mortality rates of newborn transport. A review of the literature on the field indicates a number of studies in which different pregnancy weeks and birth weights are considered. As an example of mortality prediction of preterm babies, Lucas de Silva et al. [14] studied TRIPS performance in the prediction of mortality rates. In particular, in determining the mortality risk of babies with less than 32 weeks of gestation within a seven-day period, they concluded that TRIPS was an important indicator. Arora et al. [25] also analysed the physiological effects of low birth weight during transportation using TRIPS scoring.

Crescenzi et al. [26] evaluated the achievement of a neonatal emergency transport service by using TRIPS in different gestational ages. The gestational age is divided into four groups as 22-26, 27-31, 32-36 and  $\geq 37$  weeks. In this study, the average values of pre- and post-transport TRIPS scores are examined for each group, and the success of the transport service is emphasised. However, it is confirmed that the study should be examined again by taking into account the values of mortality and morbidity. Alvarado-Socarras et al. [27] aimed to determine the important parameters affecting the mortality rate using data for 191 neonatal patients over a six-month period. As a result of the study, the neonates who weigh less than 1500 grams and have renal failure, congenital defects and higher TRIPS values have a higher mortality risk. In addition, the transport time and the quality of the ambulance reduce the mortality risk.

Lucas de Silva et al. [14] concluded that TRIPS is an important factor in determining the mortality rates. Arora et al. [25] also made use of TRIPS. In our study, the TRIPS scoring system for all pregnancy weeks was used, as in the studies of Mohamed and Aly [9] and Alvarado-Socarras et al. [27].

In the present study, using data that were not included in the TRIPS scoring (but that could be easily obtained via telephone, internet, etc.), we attempted to determine the mortality rates based on TRIPS scoring and whether or not babies would survive after being transported and treated

in the medical centre. Next, the mortality rate was obtained by ANN.

Learning, validation and test data rates were gathered as 0.8, 0.1 and 0.1, respectively, in a study predicting mortality rates of babies based on TRIPS scores and using data concerning 138 newborns such as gender, birth weight, gestation week, transportation day, transportation location and transportation distance. With the aim of determining the most appropriate layer number of the neuron number in the hidden layer, artificial neural networks were used for different neuron numbers, and for each neuron, learning, validation, test and performance scores of all systems ( $R$ ,  $R^2$  and MSE values) were obtained, as presented in Table 3. The best  $R^2$  and MSE values were obtained when the number of hidden neurons was 12. As a result, the number of hidden neurons in this study was chosen to be 12. As shown in Table 3, in the training part of the data of the 138 newborns, it was calculated that the performance regression value of the learning data is 0.9529, the performance value of the validation data is 0.9185, the performance value of the test data is 0.9497, and the entire system performance regression value is 0.9490. These regression values are given in Fig. 3. The performance values are larger than 0.90, indicating that the explanatory variables explain 90% of the variability in the output variable.

The results suggest that the input parameters that were considered will yield reliable results concerning mortality rates based on the TRIPS score and the living status of the newborns.

The proposed ANN model for this study was performed on 10 patients. For these patients, the TRIPS scores were calculated, and for the same patients, the TRIPS scores were predicted using the artificial neural network approach. The inputs from these patients involved in the artificial neural networks approach are presented in Table 4. These inputs made it possible to predict the TRIPS score. Additionally, considering the temperature, respiratory status, systolic blood pressure and response to noxious stimuli values of the same patients, TRIPS scoring was conducted, as presented in Table 4. Table 5 presents the confusion matrix for these patients.

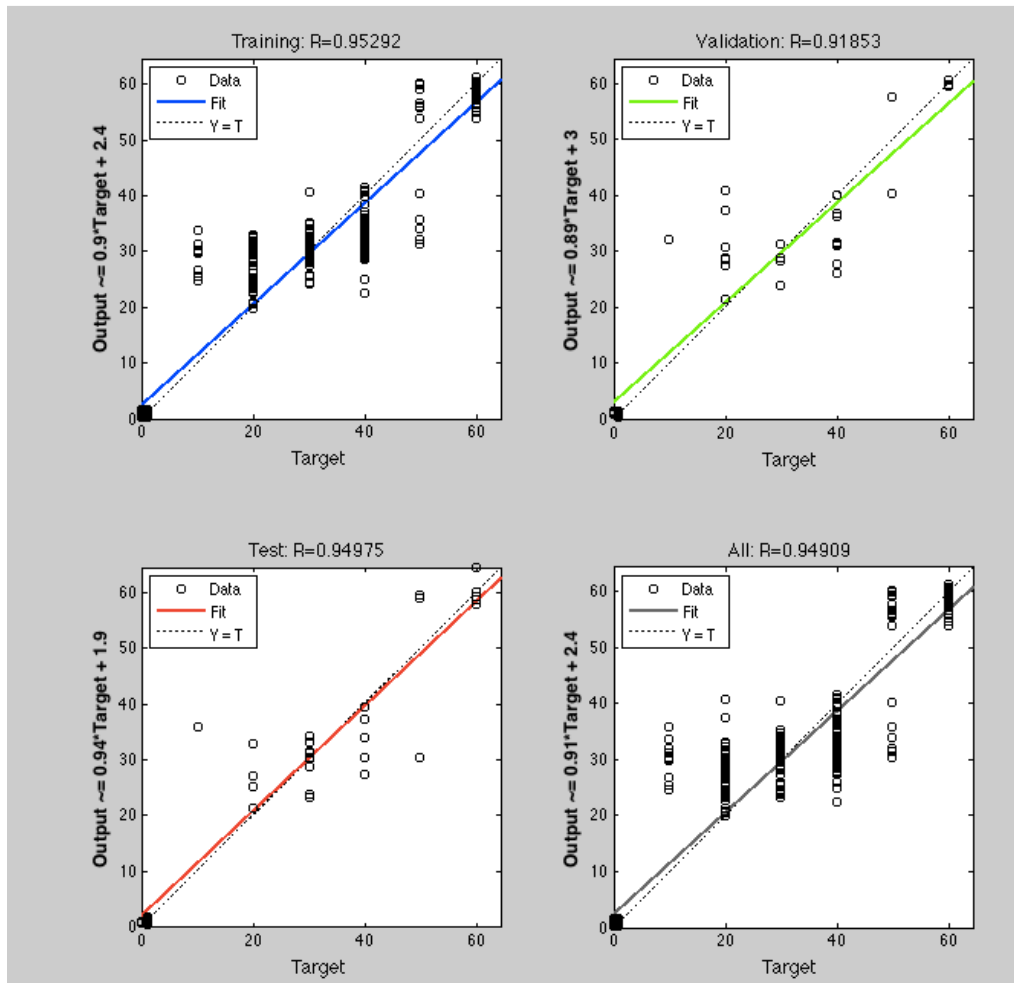
When the calculated and predicted TRIPS values in Table 4 and Table 5 are examined, nine out of 10 patients are found to have been correctly predicted. For the 10<sup>th</sup> patient, who was not correctly predicted, the TRIPS value is 0.03, and

the artificial neural network predicted value is 0.05. In TRIPS scoring, 0.03 is located in one lower category below 0.05, and one category deviation may not be significant. The predicted score in fact provides information regarding the state of the baby, suggesting that our artificial

neural network model is successful in predicting the TRIPS values. With this prediction method, it is possible to determine which transportation request will require more immediate action in the event of multiple transportation requests.

**Table 3. Artificial neural network results on different hidden layers**

Neuron number in hidden layer	Performance values					
	Learning	Validation	Test	All (R)	R <sup>2</sup>	MSE
8	0.89402	0.92878	0.87618	0.89458	0.8003	0.4793
9	0.90917	0.91332	0.8104	0.89914	0.8085	0.4363
10	0.86301	0.93636	0.91438	0.87391	0.7637	0.3833
11	0.91445	0.88454	0.91838	0.91012	0.8283	0.6115
12	0.95292	0.91853	0.94975	0.94909	0.9008	0.2062
13	0.88004	0.88744	0.85227	0.87509	0.7658	0.5472
14	0.91366	0.94508	0.87931	0.90872	0.8258	0.3787
15	0.79253	0.9034	0.79277	0.80137	0.6422	0.6815



**Fig. 3. Regression results in artificial neural networks on condition that the number of hidden neurons is 12**

**Table 4. Input, calculated and predicted output values for the new 10 patients**

Patient no	Input values						Output values	
	Gender	Gestation week (Week)	Birth weight (Gram)	Transportation day (Day)	Transportation location	Transportation distance (km)	Calculated score of TRIPS	Artificial neural network value-predicted score of TRIPS
1	Male	40	2700	5	Out-of-Province	210	0.05	0.05
2	Female	26	1150	5	Out-of-Province	210	0.18	0.18
3	Male	39	2000	2	Out-of-Province	240	0.05	0.05
4	Female	26	850	1	Out-of-Province	220	0.18	0.18
5	Male	27	800	16	Inner Province	10	0.05	0.05
6	Male	34	1800	9	Out-of-Province	130	0.03	0.03
7	Female	26	970	3	Out-of-Province	210	0.18	0.18
8	Male	26	1030	3	Out-of-Province	130	0.05	0.05
9	Male	37	2750	2	Out-of-Province	200	0.05	0.05
10	Male	28	1160	4	Out-of-Province	210	0.03	0.05



**Table 5. Confusion matrix for actual and predicted class of TRIPS**

	Values	Predicted class of TRIPS					
		0.01	0.03	0.05	0.15	0.18	0.27
Actual class of TRIPS	0.01	0	0	0	0	0	0
	0.03	0	1	1	0	0	0
	0.05	0	0	5	0	0	0
	0.15	0	0	0	0	0	0
	0.18	0	0	0	0	3	0
	0.27	0	0	0	0	0	0

#### 4. CONCLUSION

In the present study, the values of gender, birth weight, gestation week, transportation day, transportation location and transportation distance were taken as inputs, and the mortality rates based on the TRIPS score were attempted to be predicted using artificial neural networks. At the end of the predictions, the health conditions and survival possibilities of the newborns could be evaluated without actually visiting the newborns. This evaluation before transportation is of significant importance in the case of multiple requests for transportation. Accordingly, predicting the mortality rates based on TRIPS score prior to transportation will help determine which newborn is of higher vitality risk and thus requires high-priority transportation.

In addition, due to prediction of the mortality rates before transportation, the person that organises the transportation scheduling will determine the equipment on the transportation depending on the predicted mortality rate of the newborn, which will also contribute to efficient use of equipment and better transportation for the patient.

#### 5. RECOMMENDATIONS AND FUTURE DIRECTION

Number of samplings can be increased for future studies. Also model might be enhanced with an addition of equipment and staff distribution.

#### CONSENT

All authors declare that 'written informed consent was obtained from the patient (or other approved parties) for publication of this case report and accompanying images.

#### ETHICAL APPROVAL

All authors hereby declare that all experiments have been examined and approved by the appropriate ethics committee and have therefore been performed in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki.

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#### COMPETING INTERESTS

Authors have declared that no competing interests exist.

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