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Neural Networks for Early Diagnosis of Postpartum PTSD in Women after Cesarean Section

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Featured Application: Early diagnosis and warning mechanisms are essential in every health condition. The research described in this paper can provide the means for the development of medical assistance applications.

Abstract: The correlation between the kind of cesarean section and post-traumatic stress disorder (PTSD) in Greek women after a traumatic birth experience has been recognized in previous studies along with other risk factors, such as perinatal conditions and traumatic life events. Data from early studies have suggested some possible links between some vulnerable factors and the potential development of postpartum PTSD. The classification of each case in three possible states (PTSD, profile PTSD, and free of symptoms) is typically performed using the guidelines and the metrics of the version V of the Diagnostic and Statistical Manual of Mental Disorders (DSM-V) which requires the completion of several questionnaires during the postpartum period. The motivation in the present work is the need for a model that can detect possible PTSD cases using a minimum amount of information and produce an early diagnosis. The early PTSD diagnosis is critical since it allows the medical personnel to take the proper measures as soon as possible. Our sample consists of 469 women who underwent emergent or elective cesarean delivery in a university hospital in Greece. The methodology which is followed is the application of random decision forests (RDF) to detect the most suitable and easily accessible information which is then used by an artificial neural network (ANN) for the classification. As is demonstrated from the results, the derived decision model can reach high levels of accuracy even when only partial and quickly available information is provided.

Keywords: artificial neural networks; random decision forests; posttraumatic stress disorder; DSM-V; emergency cesarean section; elective cesarean section; postpartum period

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1. Introduction

Post-traumatic stress disorder (PTSD) is a mental health problem that can develop after a person goes through a life-threatening event. The disorder can develop even when the person is witnessing an event, exposed through information, or extreme repeated exposure to the workplace [1]. The disorder, regardless of the type of exposure to trauma, causes symptoms of re-experiencing, avoidance, negative cognitions in the mood, and arousal. The duration of symptoms lasts more than a month, not due to the action of any substance or physical condition and causes a significant reduction in the individual's social life [2]. Anyone can develop PTSD at any age. Women, however, are twice as likely to develop PTSD as men, showing how they are most affected by traumatic childbirth experiences, hormonal disorders, stressful life events, and domestic violence [3].

On the other hand, PTSD profile, or partial PTSD, originally used in relation to Vietnam veterans has recently been extended to trauma victims. The PTSD profile includes the most important symptoms of PTSD, but people exposed to trauma do not meet all the diagnostic criteria of the disorder. A correlation has also been found between PTSD profiles with increased rates of suicidal ideation, alcoholism, overuse of health services, and several absences from the work environment as well as a negative reduction of a person's social life [4,5].

For several years, scientists viewed the childbirth experience as a positive experience, regardless of the presence of traumatic events. In recent years, however, birth trauma has increased researchers' interest, as it has been shown that it can develop into PTSD or PTSD profile. Actually, more than 1/3 of mothers experienced their delivery as a traumatic event, while 1/4 of them will experience postpartum PTSD [6]. Some factors can increase the chance that a postpartum mother will have PTSD, such as pathology of gestation, complicated vaginal delivery, personal history of mental disorders, tokophobia, low social support, past PTSD, and cesarean section (CS) [7–10]. Postpartum PTSD symptoms are debilitating and affect the social, professional, psychological, and communication function of the mother–infant bond and her family, as well [10]. However, there are many previous and current surveys that highlight the effect of CS on maternal mental health, especially emergency cesarean section (EMCS) which show a strong correlation with postpartum PTSD compared to other types of births [11–16].

Due to the nature of the current diagnosis procedure, which is in accordance with the (DSM-V), in order to reach a conclusion, it is necessary to wait for a period of six weeks to fill up the necessary questionnaires regarding any symptoms. However, the early detection of the possibility of developing PTSD could offer medical personnel significant information to take increased precautionary measures and alleviate any symptoms in advance.

This observation is behind the motivation of the present work. More specifically, our motivation is to examine if machine learning and especially the artificial neural network (ANNs) models can be applied to predict possible PTSD cases. Our contribution is the development of an ANN model that can detect PTSD cases using a minimum amount of information and produce an early PTSD diagnosis as soon as possible.

The rest of the paper is organized as follows: Section 2 presents the related work. In Section 3, the dataset and the proposed methodology for early diagnosis of PTSD cases are described in detail. Section 4 presents the experimental study which is based on a dataset with 469 cases. Section 5 discusses the results while Section 6 concludes the paper and gives directions for future work.

2. Related Work

An early investigation of the application of ANNs as a clinical diagnostic and a modeling tool, especially for psychiatric disorders has been presented in [17]. Although many successful cases of diagnosis in general medicine, contemporary at the time of that review, have been presented, the lack of evaluation of the impact of the nature of psychiatric data, where most variables derive from dimensional rating scales, is also mentioned. A more detailed consideration of the application of ANN models to clinical decision-making exists in [18] where some issues of psychological assessment using ANNs are discussed as well. The use of ANNs in psychology-related applications, such as personality traits analysis, has also been reviewed in [19]. In general, machine learning can provide a powerful diagnostic toolset as it is demonstrated in [20].

In a similar manner to the work presented in this paper, the use of ANNs in identifying the symptom severity in obsessive–compulsive disorder (OCD) for classification and prediction has been successfully employed in [21]. The importance of timely treatment of

OCD before leading to a chronic disability is also stressed and several significant factors related to this disorder are pointed out with confirmatory factor analysis (CFA).

The potentiality of machine learning approaches with multidimensional data sets in pathologically redefining mental illnesses and also improving the therapeutic outcomes in relation to the Diagnostic and Statistical Manual of Mental Disorders (DSM) and the International Classification of Diseases (ICD) is examined in [22]. An extended related review also exists in [23,24] where open issues for AI in psychiatry are discussed as well.

3. Materials and Methods

This study took place from July to November 2019 to August 2020, at the Midwifery Department of the General University Hospital of Larisa in Greece. It was approved by the University Hospital of Larisa Ethics Commission. Approval: 18838/08-05-2019. To answer the research question, the study was designed as a prospective study between 2 groups of postpartum women (EMCS and Elective Cesarean Section (ELCS)).

3.1. Participants

The participants were all postpartum women who gave birth by the 2 types of CS and gave their written consent for their participation. A total of 469 postpartum women were examined in this research. For each case, several demographics, prenatal health, and mental health variables were collected through questionnaires that were filled through interviews during their hospitalization in the departments and 6 weeks later. The exclusion criteria of the research were difficulties at a cognitive level, other languages than Greek, and underage mothers.

3.2. Data and Measures

The data were collected in 2 stages: the first stage was the 2nd day after CS, and the second stage was the 6th week after CS. During the first stage, from 469 women, we collected medical and demographic data from the socio-demographic questionnaire and past traumatic life events from the Life Events Checklist-5 (LEC-5) of DSM-V and Criterion A from the adapted first Criterion of PTSD. At the second stage, the PTSD symptoms from the Post-Traumatic Stress Checklist (PCL-5) of DSM-V are collected (The dataset that was used can be found in: https://users.uowm.gr/chorovas/appsci/nn_ptsd.html (accessed on 20 June 2022)).

The life events checklist (LEC) is the only measure that individuals can determine different levels of exposure to a traumatic event in their lives [25]. For a PTSD diagnosis, 8 criteria must be met. For the first criterion (Criterion A), the individual must have been exposed to death, threatened death, serious injury, or sexual violence in one of the following ways: (a) direct exposure, (b) witness to the event, (c) information of the event, and (d) exposure in the working space [26]. For this study, Criterion A was adjusted accordingly. The post-traumatic stress checklist (PCL-5) is a self-report scale, which was developed to measure and evaluate PTSD and PTSD Profile symptoms [1,27]. In the present study, the postpartum women replied via telephone to 20 questions during the 6th postpartum week, corresponding to 20 symptoms of the criteria B (re-experiencing), C (avoidance), D (negative thoughts and feelings), and E (arousal and reactivity). All replies are scored on 5-point scales (range zero to four). A score of one or more in the categories of criteria B and C and two or more in categories D and E are considered PTSD symptoms. Depending on the symptoms, the postpartum women were diagnosed with (a) provisional diagnosis of PTSD and (b) PTSD profile [27,28].

The demographics, prenatal health, and mental health variables that were collected are presented in Tables 1–3 (statistical tests with IBM SPSS Statistics v.20).

Table 1. Demographic data. Counts and percentages in corresponding diagnosis.

		Diagnosis						p-Value *
		Free		Profile		PTSD		
		N	%	N	%	N	%	
v1. Residence	1. City	303	81.2%	25	6.7%	45	12.1%	0.665
	2. Village	76	79.2%	9	9.4%	11	11.5%	
v2. Age	1. ≤20	17	77.3%	0	0.0%	5	22.7%	0.08
	2. ≤25	32	76.2%	5	11.9%	5	11.9%	
	3. ≤30	77	76.2%	5	5.0%	19	18.8%	
	4. ≤35	107	80.5%	15	11.3%	11	8.3%	
	5. ≤40	121	83.4%	9	6.2%	15	10.3%	
	6. ≤45	23	95.8%	0	0.0%	1	4.2%	
	7. >45	2	100.0%	0	0.0%	0	0.0%	
v3. Family Status	0. Single	3	100.0%	0	0.0%	0	0.0%	0.551
	1. In relationship	29	72.5%	3	7.5%	8	20.0%	
	2. Married	339	81.7%	30	7.2%	46	11.1%	
	3. Engaged	6	85.7%	0	0.0%	1	14.3%	
	4. Divorced	2	50.0%	1	25.0%	1	25.0%	
v4. Educational Status	0. Primary	29	74.4%	3	7.7%	7	17.9%	0.848
	1. Jr High Sch.	22	73.3%	4	13.3%	4	13.3%	
	2. High Sch.	159	81.1%	14	7.1%	23	11.7%	
	3. Uni	140	82.4%	12	7.1%	18	10.6%	
	4. MSc	23	82.1%	1	3.6%	4	14.3%	
	5. PhD	6	100.0%	0	0.0%	0	0.0%	
v5. Occupation	1. Employee (Pub/Priv)	116	85.3%	7	5.1%	13	9.6%	0.277
	2. Freelance	52	77.6%	5	7.5%	10	14.9%	
	3. Health care	30	78.9%	5	13.2%	3	7.9%	
	4. Educators	35	81.4%	1	2.3%	7	16.3%	
	5. Household	102	82.9%	10	8.1%	11	8.9%	
	6. Unemployed	44	71.0%	6	9.7%	12	19.4%	
v6. Financial Status	1. Low	103	75.7%	11	8.1%	22	16.2%	0.399
	2. Medium	266	83.1%	22	6.9%	32	10.0%	
	3. High	10	76.9%	1	7.7%	2	15.4%	
v8. Nationality	1. Greek	343	81.1%	30	7.1%	50	11.8%	0.887
	2. Other	36	78.3%	4	8.7%	6	13.0%	
v9. Minority	0. No	356	81.7%	31	7.1%	49	11.2%	0.196
	1. Yes	23	69.7%	3	9.1%	7	21.2%	

* *p*-values refer to Pearson chi-square.

Table 2. Prenatal health variables. Counts and percentages in corresponding diagnosis.

		Diagnosis						p-Value *
		Free		Profile		PTSD		
		N	%	N	%	N	%	
v10. Parity	0. No	158	78.2%	13	6.4%	31	15.3%	0.278
	1. One birth	149	84.2%	12	6.8%	16	9.0%	
	2. >1	72	80.0%	9	10.0%	9	10.0%	
v11. Previous labor	0. No prev. labor	160	78.4%	13	6.4%	31	15.2%	0.013
	1. Vaginal	25	67.6%	3	8.1%	9	24.3%	
	2. C-section	188	85.8%	16	7.3%	15	6.8%	
	3. Vag. and CS	6	66.7%	2	22.2%	1	11.1%	
v12. Type of conception	1. Normal	342	79.7%	33	7.7%	54	12.6%	0.145
	2. IVF	37	92.5%	1	2.5%	2	5.0%	

Table 2. *Cont.*

		Diagnosis						*p*-Value *
		Free		Profile		PTSD		
		N	%	N	%	N	%	
v14. Atomic history	0. None	297	80.7%	24	6.5%	47	12.8%	0.05
	1. Thyroid	47	87.0%	3	5.6%	4	7.4%	
	2. C/V	9	75.0%	1	8.3%	2	16.7%	
	3. Neurological	5	71.4%	1	14.3%	1	14.3%	
	4. AutoImm.	7	87.5%	1	12.5%	0	0.0%	
	5. Kidney	1	50.0%	0	0.0%	1	50.0%	
	6. Tubes	1	33.3%	2	66.7%	0	0.0%	
	7. Myopia	5	100.0%	0	0.0%	0	0.0%	
	8. Other	7	70.0%	2	20.0%	1	10.0%	
v15. Gynecologic hist.	0. No	345	81.9%	29	6.9%	47	11.2%	0.39
	1. Intr.fetal demise	21	70.0%	2	6.7%	7	23.3%	
	2. Gynec.cancers	1	100.0%	0	0.0%	0	0.0%	
	3. Prem.ovarian	2	100.0%	0	0.0%	0	0.0%	
	4. Surgeries	2	66.7%	1	33.3%	0	0.0%	
	5. Death infant	5	62.5%	2	25.0%	1	12.5%	
	6. Uterine pathology	3	75.0%	0	0.0%	1	25.0%	
v16. Pathology of gestation	0. No	267	85.3%	26	8.3%	20	6.4%	<0.001
	1. Thromb/hyperem.	5	71.4%	1	14.3%	1	14.3%	
	2. Preeclampsia	38	69.1%	2	3.6%	15	27.3%	
	3. Placenta previa	13	68.4%	0	0.0%	6	31.6%	
	4. Diabetes	42	80.8%	5	9.6%	5	9.6%	
	5. Cervical insuff.	6	75.0%	0	0.0%	2	25.0%	
	6. Infection	3	50.0%	0	0.0%	3	50.0%	
	7. Premature contr.	5	55.6%	0	0.0%	4	44.4%	
v18. Full term	1. Yes	330	84.2%	31	7.9%	31	7.9%	<0.001
	2. Late preterm	43	65.2%	3	4.5%	20	30.3%	
	3. Very preterm	6	54.5%	0	0.0%	5	45.5%	
v19. Type of C-section	1. Emergency	115	63.5%	18	9.9%	48	26.5%	<0.001
	2. Programmed	264	91.7%	16	5.6%	8	2.8%	
v21. Cause of C-section	1. Previous CS	178	87.3%	17	8.3%	9	4.4%	<0.001
	2. Abnormal fet.pos.	46	88.5%	2	3.8%	4	7.7%	
	3. Twins/IVF	29	96.7%	1	3.3%	0	0.0%	
	4. Mother’s desire	20	83.3%	2	8.3%	2	8.3%	
	5. Placenta previa	7	43.8%	0	0.0%	9	56.3%	
	6. Heavy med. hist.	12	80.0%	3	20.0%	0	0.0%	
	7. Failure of labor	39	88.6%	4	9.1%	1	2.3%	
	8. Abnormal HR	37	57.8%	5	7.8%	22	34.4%	
	9. Preeclampsia	11	55.0%	0	0.0%	9	45.0%	
v22. Complications after C-section	0. None	365	84.1%	34	7.8%	35	8.1%	<0.001
	1. Bleeding	6	33.3%	0	0.0%	12	66.7%	
	2. Infection	3	50.0%	0	0.0%	3	50.0%	
	3. High blood press.	4	57.1%	0	0.0%	3	42.9%	
	4. Neuro/psychiatric	0	0.0%	0	0.0%	1	100.0%	
	5. Other	1	33.3%	0	0.0%	2	66.7%	
v23. Breastfeeding	0. No	101	66.0%	12	7.8%	40	26.1%	<0.001
	1. Yes	278	88.0%	22	7.0%	16	5.0%	
v24. NICU	0. No	319	86.9%	31	8.4%	17	4.6%	<0.001
	1. Perinatal stress	25	61.0%	1	2.4%	15	36.6%	
	2. Infection	2	50.0%	0	0.0%	2	50.0%	
	3. Prematurity	29	59.2%	1	2.0%	19	38.8%	
	4. IUGR	1	50.0%	0	0.0%	1	50.0%	
	5. Other	3	50.0%	1	16.7%	2	33.3%	

* *p*-values refer to Pearson chi-square.

Table 3. Mental health variables. Counts and percentages in corresponding diagnosis.

		Diagnosis						
		Free		Profile		PTSD		*p*-Value *
		N	%	N	%	N	%	
v13. Psych. history	0. None	353	85.9%	20	4.9%	38	9.2%	<0.001
	1. Stress disord.	13	44.8%	5	17.2%	11	37.9%	
	2. Postpartum mental disorders	9	52.9%	5	29.4%	3	17.6%	
	3. Depression	2	25.0%	4	50.0%	2	25.0%	
	4. Psych. syndromes	2	50.0%	0	0.0%	2	50.0%	
v25. Support from partner	0. No	30	44.1%	16	23.5%	22	32.4%	<0.001
	1. Yes	349	87.0%	18	4.5%	34	8.5%	
v26. Expectations	0. No	157	64.1%	33	13.5%	55	22.4%	<0.001
	1. Yes	222	99.1%	1	.4%	1	.4%	
v31. Traumatic C-section	0. No	228	99.1%	2	.9%	0	0.0%	<0.001
	1. Yes	151	63.2%	32	13.4%	56	23.4%	
v32. Criterion A1 Was your life or your child's life in danger?	0. No	328	89.1%	31	8.4%	9	2.4%	<0.001
	1. Child's	35	55.6%	3	4.8%	25	39.7%	
	2. Mother's	10	58.8%	0	0.0%	7	41.2%	
	3. Both	6	28.6%	0	0.0%	15	71.4%	
v33. Criterion A2 Any complications involving you or your child?	0. No	349	87.7%	33	8.3%	16	4.0%	<0.001
	1. Child's	20	44.4%	1	2.2%	24	53.3%	
	2. Mother's	8	50.0%	0	0.0%	8	50.0%	
	3. Both	2	20.0%	0	0.0%	8	80.0%	

* *p*-values refer to Pearson chi-square.

In total, for each case there were 70 data fields available as it is shown in Table 4.

As mentioned in Section 1, the development of a diagnostic model that could indicate early a possible PTSD case using a minimum amount of information could be very useful to prepare the health personnel for such a scenario so that appropriate measures could be taken in advance. Having this in mind we initially trained an artificial neural network (ANN) [18,23] with all the available information so that we could check whether the traditionally confirmed diagnosis could be replicated. Since that was easily achieved by a two-layered feed-forward ANN (Table 5), the focus was moved to the proper subset of data that could be used to achieve high classification accuracy. Random forest classification [29] was performed with the initial set of 70 data fields (variables). The goal was to derive Gini importance values [30] which could assist with the selection of the proper subset of variables. The criteria for the selection of these variables were the level of their direct availability with the smaller number of questions asked. This procedure resulted in having the sets of data that we used to train the ANNs models. A schematic diagram of the above processing is depicted in Figure 1.

Table 4. The total of 70 available data fields.

Description	Number of Data Fields	Coded Labels
Demographics (as shown in Table 1)	8	v1, v2, v3, v4, v5, v6, v8, v9
Prenatal health variables (as shown in Table 2)	12	v10, v11, v12, v14, v15, v16, v18, v19, v21, v22, v23, v24
Mental health variables (as shown in Table 3)	6	v13, v25, v26, v31, v32,v33

Table 4. *Cont.*

Description	Number of Data Fields	Coded Labels
Criteria A, B, C, D, E (binary variables)	5	v35, v36, v37, v38, v39
Answers to the twenty questions from DSM-V so that the PTSD score and values of Criteria B, C, D, and E are defined (values in {0,1,2,3,4}. These answers and the corresponding values for Criteria B, C, D, and E are only available six weeks after the birth.	20	v41–v60
The third question related to Criterion A (A3), number of similar stressful experiences. Min = 0, max = 11, median = 0.A Kruskal–Wallis H test showed that there was a statistically significant difference in its values between the three different diagnoses, H = 96.480, df = 2, $p < 0.001$, with a mean rank of 219.32 for free, 249.71 for profile, and 332.31 for PTSD.	1	v34
The seventeen Life Events Checklist (LEC-5) of DSM-V. Values are weighted and summed for each of the four severity options (personal, witness, other, and occupation related with weight 4.0, 3.0, 2.0 and 1.0, respectively)	17	lec_1–lec_17
The total count of LEC-5 answers. Min = 0, max = 11, median = 1. A Kruskal–Wallis H test showed that there was a statistically significant difference in its values between the three different diagnoses, H = 49.636, df = 2, $p < 0.001$, with a mean rank of 214.89 for free, 341.76 for profile, and 306.25 for PTSD.	1	v61

Table 5. The averaged confusion matrix of the initial classification results for the training phase using the complete set of the 70 variables. The accuracy is 99.6%.

	Free	Profile	PTSD	Precision	Recall (Sens.)	Specificity
Free	**341.1**	0	0	99.9%	100%	99.7%
Profile	0.2	**28.8**	1.5	100%	94.4%	100%
PTSD	0	0	**50.4**	97.1%	100%	99.6%

The corresponding results and additional details from the above methodology are presented to the following section.

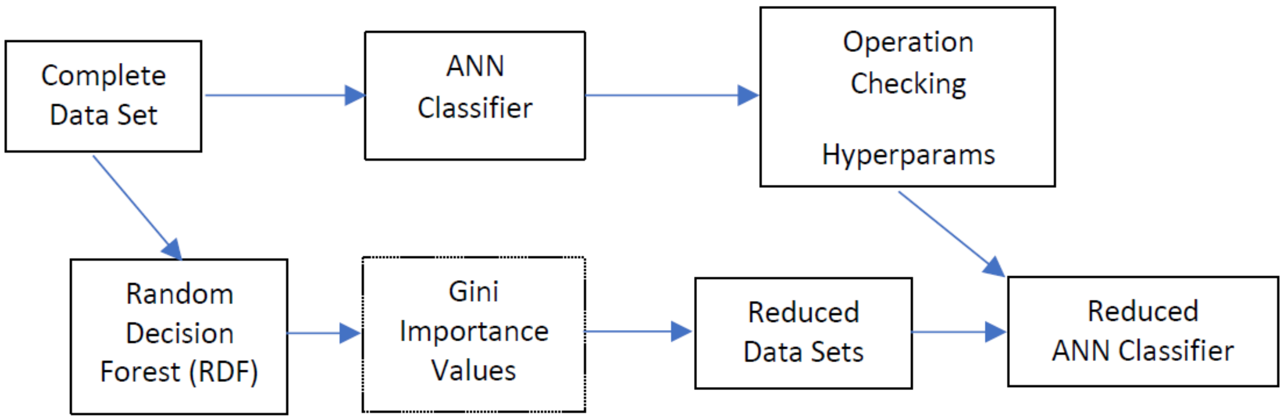

Figure 1. A schematic diagram of the methodology used.

4. Results

4.1. Initial Classification Using the ANN

As mentioned above, the complete set of the data were used initially to examine the feasibility of the reproduction of the original classification according to the DSM-V.

From the 469 cases of the collected data, 379 (80.81%) were manually diagnosed as free of symptoms, 34 (7.24%) had traces and were characterized as profile and 56 (11.94%) were diagnosed as PTSD cases. For the training and testing phases, a stratified ten-fold cross-validation scheme was employed.

The ANN was created using the PyTorch (v1.9.0 + cu11) library in Python and had a structure of seventy input units (in the case of the complete data fields as shown in Table 4), six hidden units, and three output units using three bits for the output where only one of them was set to "1" indicating the diagnosis (one hot coding). The connections were feed-forward from one layer to the next, the Sigmoid function (with $\alpha = 1.0$) was used for activation and the mean squared error (MSE) was employed from the stochastic gradient descent (SGD) optimization algorithm for training. The learning rate was set to 1.0 and the momentum to 0.9. The tuning of the hyperparameters that were used was performed on a trial-and-error base after several initial experimentations.

Initially, we estimated precision, recall, specificity, and accuracy for the complete set of the 70 variables by considering the confusion matrices and these are presented in Tables 5 and 6. Precision estimates how many positive predictions were correct. Recall estimates how many positives are correctly predicted while specificity estimates how many negatives are correctly predicted. Precision is calculated as the fraction TP/(TP + FP), the recall (sensitivity) as TP/(TP + FN), the specificity TN/(TN + FP), and the total accuracy $(TP_1 + TP_2 + TP_3)/(P_1 + P_2 + P_3)$ where TP, FP, TN, and FN are the true and false positives and true and false negatives, respectively.

Table 6. The averaged confusion matrix of the initial classification results for the testing phase using the complete set of the 70 variables. The accuracy is 92,9%.

	Free	Profile	PTSD	Precision	Recall (Sens.)	Specificity
Free	**36.9**	0.6	0.6	96.8%	97.4%	86.4%
Profile	1.1	**1.7**	0.6	60.7%	50.0%	97.5%
PTSD	0.1	0.5	**4.8**	82.8%	88.9%	97.6%

The results for both phases are averaged over ten sessions of the experiments, each one with a different initialization of the weights of the ANN. The averaged learning curve for the training process is depicted in Figure 1.

From Tables 5 and 6 and Figure 2, we can see that the ANN manages to easily learn the classification procedure of the DSM-V. However, we need to perform the same classification with as few variables as possible. Therefore, we employ the RDF importance values.

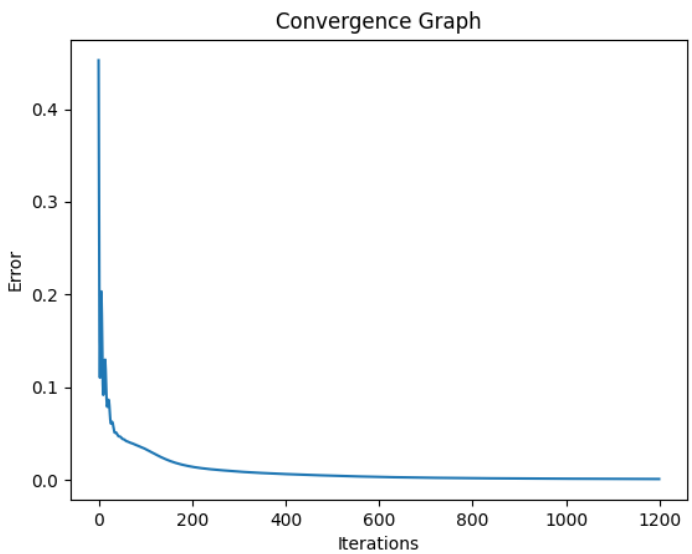

Figure 2. The convergence graph for the training with all the initial data (70 fields).

4.2. Importance Values Using Random Decision Forests

All the data from the initial set (469 × 70) were used with the random decision forests classification which was performed using the function *randomForest* from the library *randomForest* version 4.6-14 in RStudio (v1.3.1093). The number of trees was 500 and the number of variables tried at each split (*mtry*) was 20. These parameters were also selected on a trial-and-error basis. As RDF classification has a stochastic feature in its operation, ten sessions were run, and the average estimated error rate was 1,13%. The average confusion matrix is shown in Table 7.

Table 7. The averaged confusion matrix and the classification errors from the RDF.

	Free	Profile	PTSD	Class. Error	Sd of Class. Error
Free	**378**	1	0	0.002375	0.001498
Profile	1	**31**	2	0.097055	0.01421
PTSD	0	1	**55**	0.017857	3.66×10^{-18}

A powerful feature of RDF classification is that an importance vector is also returned which has the Gini importance values (mean decrease in impurity, MDI) [30] of the variables used. This is very useful for having an idea of what variables contribute more to the classification process as the higher the Gini values the higher the importance of the variables. This is profound in our research as our aim was to reach a competitive level of classification using as less and more directly acquired, variables as possible.

The Gini values for the 70 variables sorted from highest to lowest can be seen in Figure 3 and in Table 8 for more precision.

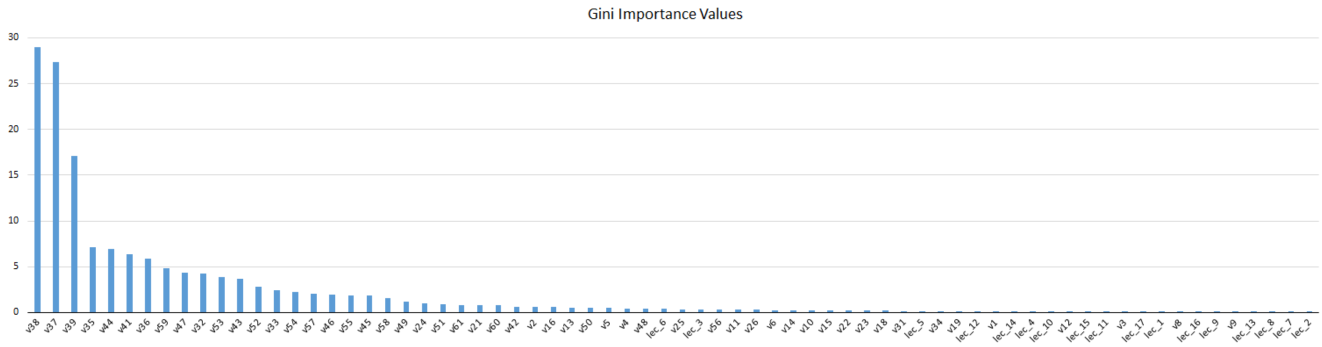

Figure 3. The averaged Gini importance values of the 70 variables in descending order.

Table 8. The averaged Gini importance values of the 70 variables in descending order [1]. Bolded variables are only available after six weeks of birth.

Variable	Gini Value	Variable	Gini Value	Variable	Gini Value	Variable	Gini Value
v38	28.98435	**v45**	1.8905019	lec_3	0.31930649	lec_4	0.137412479
v37	27.394505	**v58**	1.5943305	**v56**	0.30413895	lec_10	0.12593543
v39	17.084163	**v49**	1.1418203	v11	0.30269473	v12	0.120028475
v35	7.1403067	v24	1.00739209	v26	0.29636865	lec_15	0.107513023
v44	6.971652	**v51**	0.9250898	v6	0.27196558	lec_11	0.101853315
v41	6.3785479	v61	0.81900432	v14	0.26559605	v3	0.101409277
v36	5.8372447	v21	0.81722037	v10	0.25888349	lec_17	0.094143941
v59	4.8650734	**v60**	0.81011046	v15	0.2548879	lec_1	0.084016984
v47	4.3128049	**v42**	0.63748018	v22	0.24198349	v8	0.082011903
v32	4.2619363	v2	0.62349169	v23	0.21767294	lec_16	0.080463707

Table 8. *Cont.*

Variable	Gini Value	Variable	Gini Value	Variable	Gini Value	Variable	Gini Value
v53	3.8501501	v16	0.60897038	v18	0.1983336	lec_9	0.05289523
v43	3.6749819	v13	0.54351801	v31	0.17640773	v9	0.045091486
v52	2.8472892	**v50**	0.53564906	lec_5	0.17548751	lec_13	0.028551434
v33	2.4381206	v5	0.49679806	v34	0.17496421	lec_8	0.011308693
v54	2.2139708	v4	0.41331847	v19	0.166634565	lec_7	0.008951235
v57	2.0267311	**v48**	0.39974051	lec_12	0.14626491	lec_2	0.004792534
v46	1.9955999	lec_6	0.37660294	v1	0.14314126		
v55	1.8907127	v25	0.36428793	lec_14	0.142114515		

[1] The variable coding scheme is mentioned in Table 4.

4.3. Classification Using a Subset of the Available Data

The values in Table 8 show an expected high level of importance to the variables that are used directly for the typical diagnosis procedure in DSM-V (indicated by bold variable labels). As these are only available after six weeks, our effort is to avoid them and concentrate on what is quickly and easily acquired with as less questions as possible. This gives us the list of candidate variables listed in Table 9.

Table 9. The list of 24 candidate variables for direct diagnosis sorted by Gini importance.

Label	Description	Comments
v35	Criterion A	This is activated upon at least a positive answer in v32 and/or v33 (below). The number of the events (v34 in Table 4) is related to this criterion but is not considered for its activation.
v32	Criterion A1 Was your life or your child's life in danger?	Easy to check in hospital
v33	Criterion A2 Any complications involving you or your child?	Easy to check in hospital
v24	NICU	Easy to check in hospital
v61	The total count of LEC-5 answers	Easy to count from LEC answers
v21	Cause of C-section	Easy to check in hospital
v2	Age	Easy
v16	Pathology of gestation	Info available from surveillance dossier
v13	Psych. history	Info available from surveillance dossier
v5	Occupation	Easy
v4	Educational status	Easy
lec_6	Physical assault	Part of LEC questionary
v25	Support from partner	Easy
lec_3	Transportation accident (car, train, boat)	Part of LEC questionary
v11	Previous labor	Easy
v26	Expectations	Question, subjective
v6	Financial status	Question
v14	Atomic history	Info available from medical history
v10	Parity	Easy
v15	Gynecologic hist.	Info available from medical history
v22	Complications after C-section	Easy
v23	Breastfeeding	Easy but not directly available
v18	Full term	Easy
v31	Traumatic C-section	Easy

All the twenty-four variables that are presented in Table 9 were used to construct eight data sets (called D1–D8) in steps of three. The variables in each dataset and the corresponding sum of the Gini values of these variables can be seen in Table 10.

Table 10. The eight datasets that were created from the variables in Table 9 and the corresponding sum of their Gini values. "1" means the variable is included in the dataset.

	35	32	33	24	61	21	2	16	13	5	4	L6	25	L3	11	26	6	14	10	15	22	23	18	35	
D1	1	1	1																						13.84
D2	1	1	1	1	1	1																			16.48
D3	1	1	1	1	1	1	1	1	1																18.26
D4	1	1	1	1	1	1	1	1	1	1	1	1													19.55
D5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1										20.53
D6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1							21.37
D7	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1				22.12
D8	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	22.72

The results concerning the precision, recall (sensitivity), specificity, and accuracy during the training and testing phases in a stratified ten-fold cross-validation scheme can be seen in Tables 11 and 12 and Figures 4 and 5.

Table 11. The results during the training phase for the eight partial datasets (D1–D8) and for the complete set of the 70 variables (bolded values). Stratified ten-fold cross validation is applied.

	Training Phase									
	PTSD			Profile			Free			
	Prec.	**Recall**	**Spec.**	**Prec.**	**Recall**	**Spec.**	**Prec.**	**Recall**	**Spec.**	**Acc.**
D1	0.63	0.55	0.96	0.00	0.00	1.00	0.86	0.95	0.34	0.84
D2	0.70	0.65	0.96	0.00	0.00	1.00	0.87	0.96	0.41	0.85
D3	0.72	0.70	0.96	0.57	0.12	0.99	0.89	0.96	0.50	0.86
D4	0.74	0.76	0.96	0.66	0.16	0.99	0.90	0.96	0.56	0.88
D5	0.77	0.77	0.97	0.77	0.32	0.99	0.92	0.97	0.64	0.90
D6	0.83	0.83	0.98	0.79	0.35	0.99	0.93	0.97	0.68	0.91
D7	0.83	0.83	0.98	0.79	0.35	0.99	0.93	0.97	0.68	0.91
D8	0.81	0.79	0.97	0.77	0.34	0.99	0.92	0.97	0.66	0.90
All-70	**0.97**	**1.00**	**0.99**	**1.00**	**0.94**	**1.00**	**0.99**	**1.00**	**0.99**	**0.99**

Table 12. The results during the testing phase for the eight partial datasets (D1–D8) and for the complete set of the 70 variables (bolded values). Stratified ten-fold cross validation is applied.

	Testing Phase									
	PTSD			Profile			Free			
	Prec.	**Recall**	**Spec.**	**Prec.**	**Recall**	**Spec.**	**Prec.**	**Recall**	**Spec.**	**Acc.**
D1	0.58	0.52	0.95	0.00	0.00	1.00	0.85	0.94	0.32	0.83
D2	0.61	0.51	0.96	0.00	0.00	1.00	0.86	0.96	0.33	0.83
D3	0.64	0.63	0.95	0.50	0.06	1.00	0.88	0.94	0.43	0.84
D4	0.64	0.64	0.95	0.60	0.09	1.00	0.88	0.94	0.44	0.85
D5	0.67	0.63	0.96	0.38	0.15	0.98	0.89	0.94	0.50	0.85
D6	0.67	0.66	0.96	0.54	0.21	0.99	0.89	0.94	0.52	0.86
D7	0.67	0.66	0.96	0.54	0.21	0.99	0.89	0.94	0.52	0.86
D8	0.65	0.63	0.95	0.43	0.18	0.98	0.89	0.94	0.51	0.85
All-70	**0.83**	**0.89**	**0.98**	**0.61**	**0.50**	**0.97**	**0.97**	**0.97**	**0.86**	**0.93**

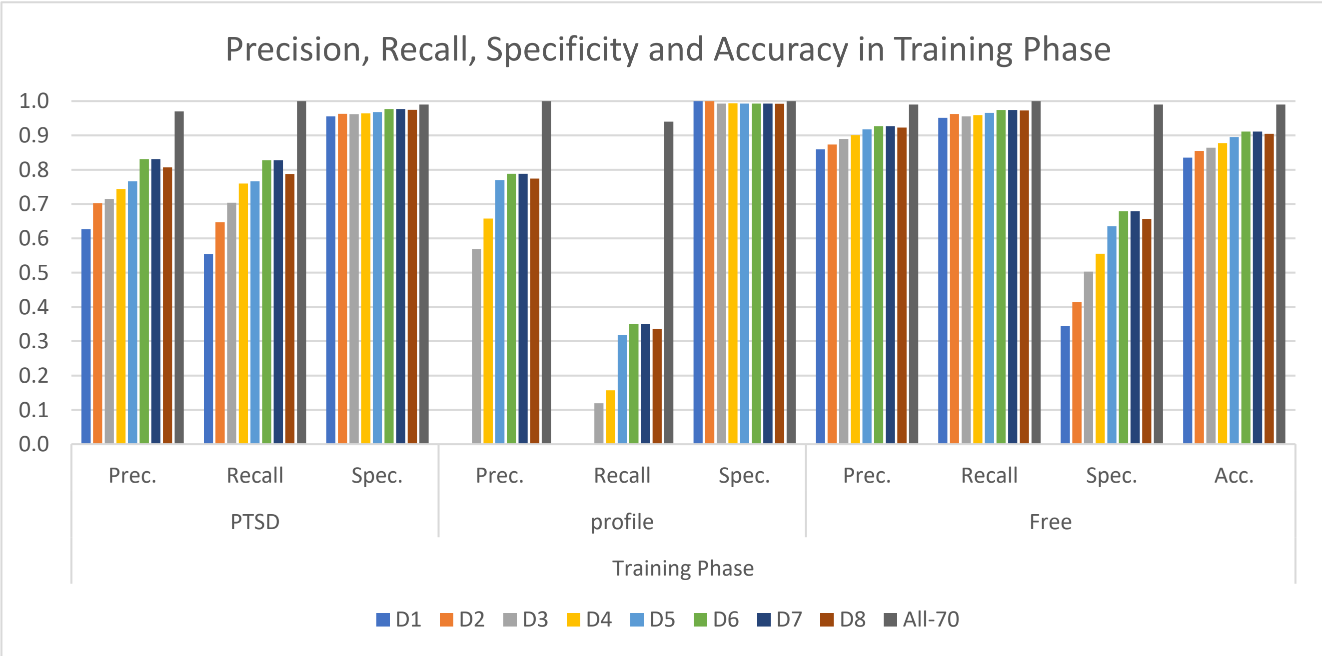

Figure 4. The precision, recall (sensitivity) and specificity for each class and dataset and the accuracy for the training phase.

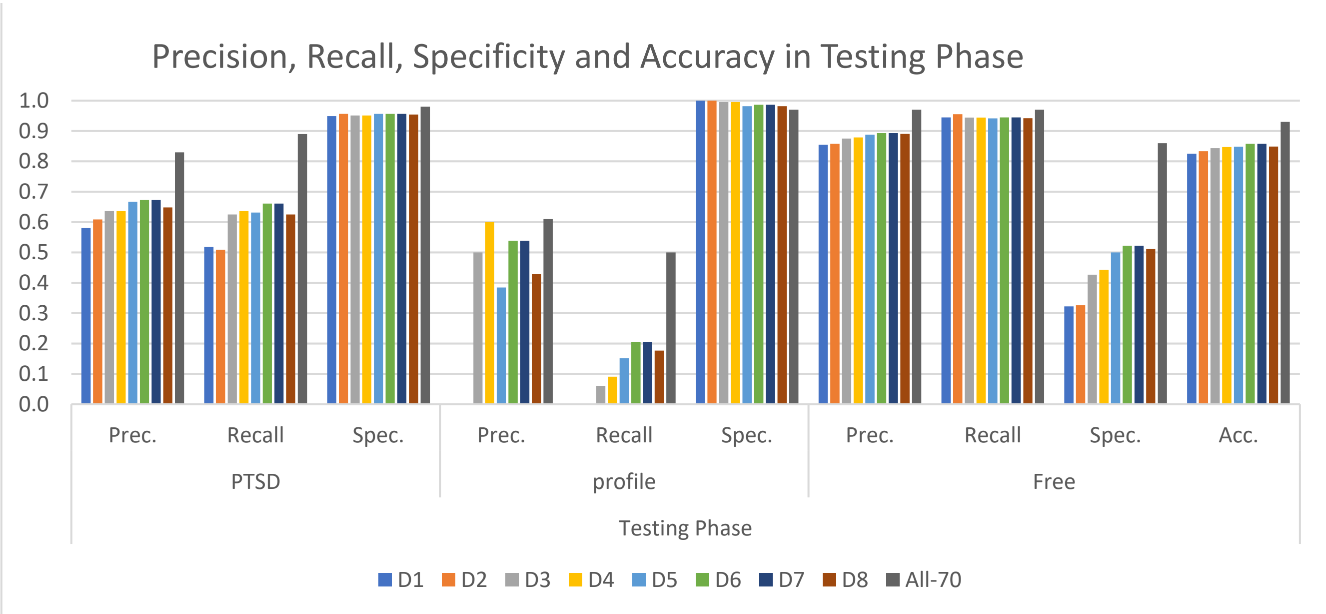

Figure 5. The precision, recall (sensitivity), and specificity for each class and dataset and the accuracy for the testing phase.

In order to have an idea about the best level of classification that could be achieved with RDF using only those variables of the complete set which are not related to DSM-V, (i.e., v41–v60 and v36–v39), ten sessions were run using the complete dataset for training. Comparing the classification errors in Table 13 (which is one recall) with the best values for recall in Table 12 we can observe a slightly better performance from the ANN using datasets D6 and D7 with only 18 and 21 variables, respectively. This is an indication of the validity of the variable selection method that was performed based on Table 8.

Table 13. The averaged confusion matrix and the classification errors from the RDF using the 46 variables remaining after removing the (20 + 4) ones directly related to the DSM-V. The complete dataset is used for the training.

	Free	Profile	PTSD	Class. Error	Sd of Class.Error
Free	**357.8**	6.6	14.6	0.05594	0.00389
Profile	25.9	**6.7**	1.4	0.80294	0.03410
PTSD	21.6	0.9	**33.5**	0.40179	0.02560

5. Discussion

The subject of the present study was to present a model that can produce an early diagnosis to detect and alarm a possible case so that proper measures can be taken as soon as possible. According to our findings, emergency cesarean section, pathology of gestation, preterm birth, the inclusion of neonate in NICU, absence of breastfeeding, psychiatric history, expectations from childbirth, and support from the partner are included in the set of important decision factors.

Additionally, as it can be seen from the results (graphs in Figures 4 and 5, Tables 11 and 12), the ability of the ANN model to arrive at a correct conclusion is demonstrated at a very satisfactory level (around 97% in training and 94% in testing) for the cases which are free of symptoms. For the cases that are PTSD diagnosed, the recognition level reaches 83% in training and 66% in testing. The area in between the above two categories has a low percentage of recognition and it collects the PTSD profile cases. As it can be observed from the results, the PTSD profile cases are the only ones that really need the late questionnaires data (after 6 weeks). According to the above, a policy that could be followed to arrive at a conclusion as soon as possible is to characterize a case that is not classified as free of symptoms as a possible PTSD case. If the case is indeed classified as PTSD, then such a scenario would probably denote an increased potentiality for the appearance of PTSD symptoms after six weeks when the second part of the data is collected. More focused treatment in such a case could be applied and this can start six weeks in advance, providing a beneficial period of medical care.

The use of random decision forests for associating an importance value for each data field is very useful as well. The ordering of the early accessible variables according to their Gini values in Table 9 is the result of that process and it can be noted that this ordering is indeed profound. Criterion A, which constitutes a basic decision factor also in the typical DSM diagnosis, is ranked first and its related parts (A1 and A2) are just after that. Although there is one more datum field related to Criterion A, (v34, number of similar stressful experiences) we decided not to use this as it requires extra effort from the side of the woman in order to be defined. The rest of the data fields that are used for the datasets are all important and this can be shown by the gradual increase in PTSD sensitivity which is noticed in the training phase (Figure 4). This is expected and it denotes the usefulness of the extra information which is added to every dataset. This information increase is also depicted as the sums of the Gini values of the datasets in Figure 6.

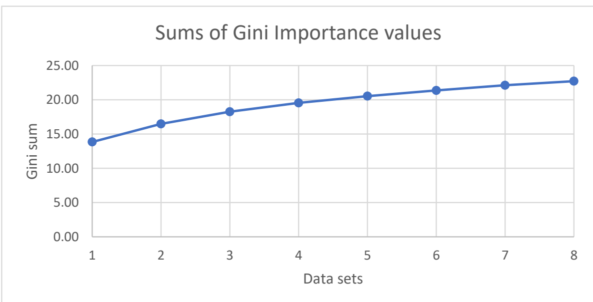

Figure 6. The graph of the sums of Gini importance values in the eight datasets (D1–D8) of Table 10.

6. Conclusions

Our aim for this research was to examine whether the use of ANN modeling for describing the classification process of postpartum PTSD could be useful to provide a diagnostic model for the early detection of possible cases. The high accuracy that is obtained using as little and as readily available information as possible demonstrates that this is possible, and this marks a successful scenario for the application of ANNs in psychological data modeling. Future research could incorporate additional machine learning tools for the classification to obtain even more precise classification percentages. The development of mobile device applications to make the process faster would be also desirable. The benefit for the persons that would finally be diagnosed positively is important as well, since the extra period gained could be used in favor of their preliminary treatment.

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