Advances In Multidisciplinary & Scientific Research
AIMS Research Journal
A Multidisciplinary & Interdisciplinary Journal

Vol. 11 No. 3, September , 2025

Expert System for Postpartum Diagnosis

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ABSTRACT

This study presents work on machine learning algorithm system than enhances the decision making for the diagnosis of postpartum depression. There exist several studies that have been reported on the diagnosis (manual or automation) of postpartum depression, the risk factors and tools for effective management and treatment of affected persons. To overcome these challenges, this study focuses on improving the accuracy paradigm for clinicians in diagnosing postpartum depression through simplification of symptoms as represented in the manual tool and specification of the type of PPD because of its complex nature and availability of related data. The study sequentially implemented the goal with the ultimate objective of implementing a system for postpartum depression diagnosis.

Keywords: Postpartum Depression, Diagnosis, Symptoms, Mood Disorder, Pathogenesis etc.

Aims Research Journal Reference Format:
Osaretin & Obahiagbon, K.O. (2025): Expert System for Postpartum Diagnosis. Advances in Multidisciplinary Research Journal. Vol. 11 No. 3, Pp 1-14. www.isteams.net/aimsjournal. dx.doi.org/10.22624/AIMS/V11N3P1

1. INTRODUCTION

Postpartum major depression is a disorder that is often unrecognized and must be distinguished from “baby blues”. Some women with postpartum major depression may experience suicidal ideation or obsessive thoughts of harming their infants, but they are reluctant to volunteer this information unless asked directly (Kathryn *et al*., 2010). Psychotherapy or selective serotonin reuptake inhibitors may be used to treat the condition. In patients with moderate to severe postpartum major depression, psychotherapy may be used as an adjunct to medication. No evidence suggests that one antidepressant is superior to others. Antidepressants vary in the amount secreted into breast milk. If left untreated, postpartum major depression can lead to poor mother-infant bonding, delays in infant growth and development, and an increased risk of anxiety or depressive symptoms in the infant later in life. The term “postpartum depression” commonly includes major and minor depression, which differ in severity and prognosis, and have a combined incidence of 7 to 15 percent in the first three months postpartum Gaynes *et al*., 2001).

The overall incidence of postpartum major depression is 5 to 7 percent in the first three months, suggesting that postpartum women have rates of major depression similar to those in the general population. However, specific risk factors significantly increase rates of postpartum major depression for a subset of women (Gaynes et al., 2005). The strongest risk factor is a history of postpartum major depression with a previous pregnancy. Other important risk factors include antenatal depressive symptoms (relative risk [RR] = 5.6), a history of major depressive disorder (RR = 4.5), poor social support (RR = 2.6), major life events or stressors during pregnancy (RR = 2.5), and a family history of postpartum major depression (RR = 2.4). 5–7 Women with gestational diabetes (Kozhimannil et al., 2009) and who give birth to multiples may also be at higher risk of postpartum major depression (Choi et al., 2009).

Socioeconomic status and obstetric complications have not been shown consistently to be risk factors for postpartum major depression (Johnstone *et al*., 2001).

1.1 Postpartum Depression

Despite being a growing public health concern that affects nursing mothers, postpartum depression (PPD) has not received much attention in primary health care settings. Because most medical professionals focus on physical ailments, they commonly miss the diagnosis because it is exceedingly difficult to make. Due to lack of standardization in the methodological parameters used in research, the prevalence of PPD varies greatly. Such variations in study populations, diagnostic techniques, current models and systems for diagnosis are frequently constrained in terms of robustness, choice of data, deployment, timely and accurate diagnosis based on clinical symptoms, and the postpartum period taken into account. According to Jegede (2022) and Zhang et al. (2020), the disease is incorrectly diagnosed when certain important PPD symptoms are not included. Because mental diseases have sub-forms that do not accurately describe the specific postpartum depression the patient experiences and obstruct appropriate treatment. Existing diagnostic approaches have been classified as (i) intelligent or non-intelligent (ii) limited in information (e.g., "depressed" or "not depressed"). However, this paper proposed a more complex and trustworthy model for the diagnosis of postpartum depression, a type of major depression, using an artificial neural network algorithm and the inclusion of widely acknowledged, validated medical list symptoms with salient indicators, simplified symptom tags, which will be implemented on a reliable open-source package and library for python and machine learning applications.

2. RELATED WORKS

Coll *et al.* (2019) in their study found that Moderate-intensity exercise during pregnancy did not lead to significant reductions in postpartum depression. However, there was a significant amount of noncompliance with the intervention procedure, which could have caused people to underestimate the potential advantages of exercise. Eduardo *et al.* (2019) carried out a systematic review to critically analyze the studies that explored preterm birth as risk factor for postpartum depression. Their findings highlighted the importance of maternal mental health care, as preterm birth experience seem to affect both babies and mothers. Azad *et al.* (2019) stated that the aim of their study was to assess the burden and risk factors of PPD among the urban slum women. However, PPD was not linked in the research to mother-in-law, poverty, or other child-related characteristics.

Vaezi *et al.,* (2019) investigated the prevalence of maternal postpartum depression and its association with social support. According to the study, postpartum depression is less likely to arise when a woman has a larger social network. To prevent postpartum depression, it is advised that families be made aware of the critical role that social support plays in health and that it be strengthened in all facets of medical treatment. By summarizing both clinical and fundamental science research findings. Payne and Maguire (2019) outlined the many potential patho-physiological pathways contributing to postpartum depression. The authors suggested that a range of biomarkers, including genetic and epigenetic variables, biochemical factors, neuro-inflammatory alterations, and circuit-level changes, could be used to identify individuals who are at risk for postpartum depression. Yin *et al*. (2019) examined User-generated content (UGC) in online contexts as a way to learn about a person's health state outside of clinical settings. The study thoroughly examined the usefulness of using machine learning (ML) approaches to user-generated content (UGC) for personal health investigations, and it concluded that machine learning might be used to UGC to describe and infer personal health.

Shatte *et al.,* (2019) reviewed how the application of Machine Learning to mental health has demonstrated a range of benefits across the areas of diagnosis, treatment and support, research, and clinical administration. With the majority of studies identified focusing on the detection and diagnosis of mental health conditions, it is evident that there is significant room for the application of Machine Learning to other areas of psychology and mental health. Frogner *et al.,* (2019) presented a machine learning approach to detect depression using a dataset with motor activity recordings of one group of people with depression and one group without, i.e., the condition group includes 23 unipolar and bipolar persons, and the control group includes 32 persons without depression. Such data would be helpful in the field of psychology because it can relate to various mental health issues such as changes in mood and stress. Horowitz et al. (2019) argued that Mother-Baby Interaction (MBI) Therapy should be a required supplemental treatment for PPD and other perinatal mental health issues. Deirdre (2020) examined Psychiatric disorders in the postpartum period and suggested administering the Edinburgh Postnatal Depression Scale as a screening tool for postpartum depression detection. The limitation here is that some women may lie while taking the screening test.

Räisänen *et al.* (2020) found out that a history of depression was found to be the most important predisposing factor of postpartum depression. Negative pregnancy outcomes, particularly if the woman had a doctor-diagnosed dread of delivering, increased the likelihood of postpartum depression in women who had never experienced depression before. Uban and Rosso (2020) used multi-dimensional features to represent various levels of the language, including content, style and emotion in the detection and the prediction of depression levels, based on social media text data. They explored with several deep learning architectures, such as transformers and hierarchical attention networks, where there was more training data available. They also experimented with various experimental setup tactics. Zhang *et al.* (2021) developed a machine learning algorithm for predicting the risk of postpartum depression among pregnant women. To assure model performance and enable future point-of-care risk prediction, a framework comprising data extraction, processing, and machine learning was created to choose a minimal list of characteristics from the EHR datasets. Despite this, the study was not thorough since the incidence of PPD in the study data was based on medication use and was most likely lower than the prevalence of the condition.

Mufidati and Suryono (2021) employed the rule-based method to diagnose postpartum depression and the expert system to input symptoms data that will result in diagnoses. Based on input from experts connected to the diagnosis the system is working on, the system automatically creates output of proposed treatments. The Randomized Control Trial approach was used in this study along with a Control Group Pre and Post Tests Design. Andersson *et al.* (2021) leveraged the power of clinical, demographic, and psychometric data to assess if machine learning methods can make accurate predictions of postpartum depression. The purpose of the project is to apply machine learning techniques to identify women who are likely to have depression symptoms at 6 weeks postpartum based on clinical, demographic, and psychometric questionnaire data that is accessible after childbirth.

Hochman *et al.* (2021) developed and validated a machine learning-based PPD prediction model utilizing electronic health record (EHR) data, and identified novel PPD predictors. They also opined that machine learning-based models incorporating EHR-derived predictors, could augment symptom-based screening practice by identifying the high-risk population at greatest need for preventive intervention, before development of PPD. Zulfiker *et al.,* (2021) investigated six different machine learning classifiers using various socio-demographic and psycho-social information to detect whether a person is depressed or not.

Besides, three different feature selection methods, such as Select K-Best Features (SelectKBest), Minimum Redundancy and Maximum Relevance (mRMR), and Boruta feature selection algorithm have been used for extracting the most relevant features from the dataset. Levinson *et al.,* (2022) carried out a study to determine the potential risk factor for emergence of PPD in the mothers whose infant where admitted to the NICU. The likelihood of postpartum depression screening in a local perinatal center, as well as an assessment of the relationship between maternal stress levels, co-morbidities specific to the neonatal intensive care unit (NICU), and PPD screening scores, may have an impact on the incidence of positive PPD screening among NICU mothers.

2.1 Expert System

Expert systems are computer programs aiming to model human expertise in one or more specific knowledge areas. They usually consist of three basic components: a knowledge database with facts and rules representing human knowledge and experience; an inference engine processing consultation and determining how inferences are being made; and an input/output interface for interactions with the user. According to Metaxiotis and Samouilidis (2000), expert systems can be characterized by:

1. Using symbolic logic rather than only numerical calculations;
2. The processing is data-driven;
3. A knowledge repository housing specific and well-defined content within a particular domain of knowledge; and
4. The capacity to present its findings in a manner that is comprehensible to the user.

Oliver (2010) described an expert system as a computer program or application designed to address complex problems that would typically necessitate extensive human expertise. It is imperative for an expert system to employ predefined and specialized knowledge to successfully emulate human reasoning. Additionally, expert systems harness human knowledge to resolve issues that typically demand human intelligence. These expert system applications find utility across a range of domains and areas of expertise, including but not limited to agriculture, education, environment, law, manufacturing, medicine, and power systems.

Knowledge Representation

In the realm of artificial intelligence, various forms of knowledge representation exist. Nevertheless, expert systems predominantly rely on what are commonly known as rule-based systems. Nevertheless, some adaptations have been made to deterministic rules to accommodate uncertainties and ambiguities.

“If … Then …Rules”

The main form of knowledge employed in traditional expert systems is "if... then... rules." As noted above those rules are used to capture heuristic reasoning that experts apparently often employ. However, over time researchers began to develop and integrate alternative forms of knowledge representation, such as frame-based or case-based reasoning (Aamodt and Plaza, 1994) into their systems. Systems that combined several forms of information were frequently referred to as hybrid systems or named after a specific knowledge representation, such as case-based. According to Wikipedia, automated reasoning and knowledge representation go hand in hand since one of the key goals of formally describing knowledge is the ability to reason about it, draw conclusions, and claim new knowledge.

Activity/Task of the System

Another argument in favor of designating a system as an "expert system" was that it successfully carried out a task that had previously been done by professionals. When solving problems, such as choosing a wine to go with dinner, experts tend to utilize organized reasoning strategies that may be represented.

Level of Performance of the System

An expert system operates continuously without lag or mistakes. It imitates human expertise to make decisions that are accurate and effective. As a result, a system must carry out tasks like a human expert in order to be called an expert system.

System Dependence

Expert systems are reliant on the body of information in a certain field and apply that knowledge to the specific circumstances of the situation at hand. Heuristic information, or general guidelines utilized by human experts working in the field, is also included in the knowledge base of an expert system. The system ceases to be an expert system, however, when environmental evaluations of situations and accompanying data input are often still handled by individuals. Negnivitsky (2005) identified five (5) commonly used expert systems: Rule-based expert systems (RBES), Case-based expert systems (CBES), Frame-based expert systems (FBES), Artificial neural network expert systems (ANNES), Fuzzy logic expert systems (FLES) and probabilistic expert systems (PES). These systems are now widely used in hospitals and clinics, transportation, production etc. And they are proved to be very useful tool for accurate and effectiveness in making decisions. In building expert systems, Bullinaria (2005) identified seven components that are needed: Expert, Knowledge acquisition system, Knowledge Base of facts, rules and heuristics, inference engine, User interface, user and, knowledge engineer, all interacting to accomplish a task as shown in figure 2.3

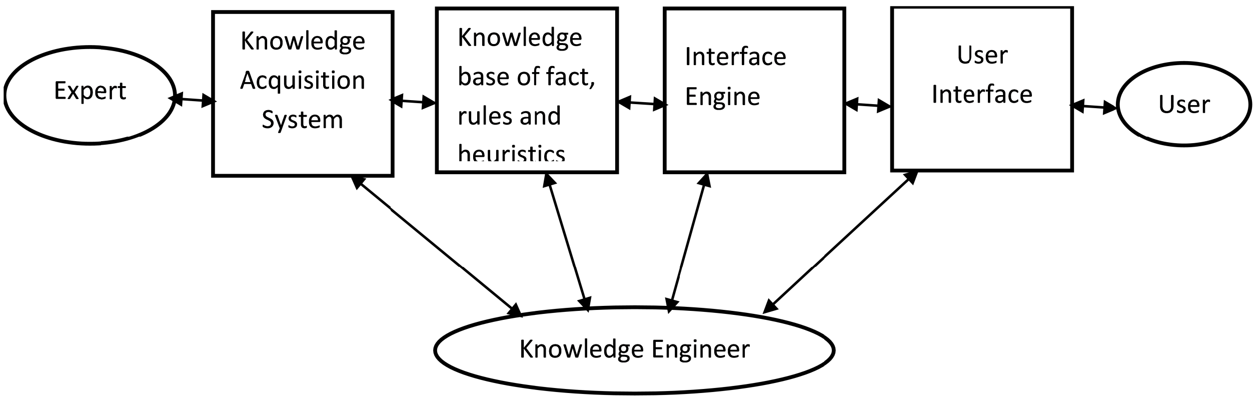

Figure 2.3: Component of Expert Systems

2.2 Knowledge Acquisition System

The expert has the capability to input their information or expertise into the expert system using the knowledge acquisition component, and can then edit it as and when necessary. Historically, the role of the knowledge engineer has held substantial importance in this procedure. However, automated technologies that facilitate direct communication between the expert and the system are gaining increasing popularity.

The process of acquiring knowledge typically unfolds in three primary phases:

1. Knowledge elicitation involves structured interactions between the expert and the knowledge engineer or program to systematically extract the expert's knowledge.
2. The acquired knowledge is typically preserved in a format that is easily understandable to humans.
3. Subsequently, this intermediate representation of the knowledge is transformed into an executable format, such as production rules, which the inference engine can then handle. In practice, many iterations through these three stages are usually require

Knowledge Base

Knowledge is a key factor in the performance of intelligent systems. A knowledge base serves as a unique type of database dedicated to knowledge management, offering a platform for the gathering, structuring, sharing, searching, and application of information. In simpler terms, it acts as a storage facility for information within the expert system.

Inference Engine

This component serves as the 'intellect' or 'brain' of the system and governs the manner in which the IF-THEN rules are applied to the available facts. In practical scenarios, this functionality should support the gathering of additional information from the system's user. The user can be prompted for supplementary input through a natural language interface, which can then be employed to refine a hypothesis or resolve conflicts among existing competing hypotheses. The inference engine conducts the reasoning process by which the expert system arrives at a solution and establishes connections between the rules stored in the knowledge base and the facts supplied in the database.

User Interface

The expert system user interface typically consists of two fundamental elements:

1. The Interrogation Component: This manages the interaction with the user and allows for the input of any measured data into the system. For instance, it may engage the user in a series of inquiries or retrieve data from a file containing test results.
2. The Elucidation Component: This delivers the system's solution and enhances transparency by offering the user insights into its reasoning process. For instance, it can present the outcome along with the sequence of rules employed in reaching that conclusion. Alternatively, it can elucidate why a conclusion could not be reached.

User

The end-user is a person who uses the expert system when it is developed. The user might be a clinician (expert or novice) diagnosing a patient from any other domains. Each of these expert system users possesses unique requirements that the system should cater for. The ultimate approval of the system hinges on the contentment of the user. It is imperative that the user not only trusts the expert system's capabilities but also finds it user-friendly. Consequently, the design of the expert system's user interface plays a pivotal role in the project's triumph, and the input from end-users in this regard can be immensely significant.

Knowledge Engineer

A knowledge engineer is an individual skilled in the design, construction, and validation of an expert system. This person bears the responsibility of identifying a suitable task for the expert system. They conduct interviews with the domain specialist to gain insights into the problem-solving approach for a specific issue. Through these interactions, the knowledge engineer discerns the reasoning techniques employed by the expert to manage facts and rules, subsequently determining how to represent them within the expert system.

Following this, the knowledge engineer makes choices regarding development software, an expert system framework, or programming languages to encode the knowledge (sometimes even performing the encoding personally). Lastly, the knowledge engineer undertakes the tasks of testing, refining, and seamlessly integrating the expert system into the operational environment. Consequently, the knowledge engineer's commitment to the project extends from the initial design phase to the final deployment of the expert system, and they may remain engaged in its maintenance even after project completion..

Expert

The domain specialist represents an individual with significant knowledge and proficiency, possessing the capability to address challenges within a particular field or sphere. This individual holds the utmost mastery within the designated domain. It is imperative to record this wealth of expertise within the expert system. Consequently, the specialist should possess the ability to convey their knowledge effectively, exhibit a willingness to engage in the development of the expert system, and dedicate a substantial portion of their time to the project. The domain specialist assumes the pivotal role within the expert system development team.

3. USE-CASE DESIGN

Use-case diagrams aid in capturing system requirements and depict a system's behavior in UML. The scope and high-level functions of a system are described in use-case diagrams. The interactions between the system and its actors are also depicted in these diagrams. Use-case diagrams show the actors and the use cases to show what the system performs and how it is used by the actors. The interaction between the users and administrator with respect to the ANN algorithm were illustrated

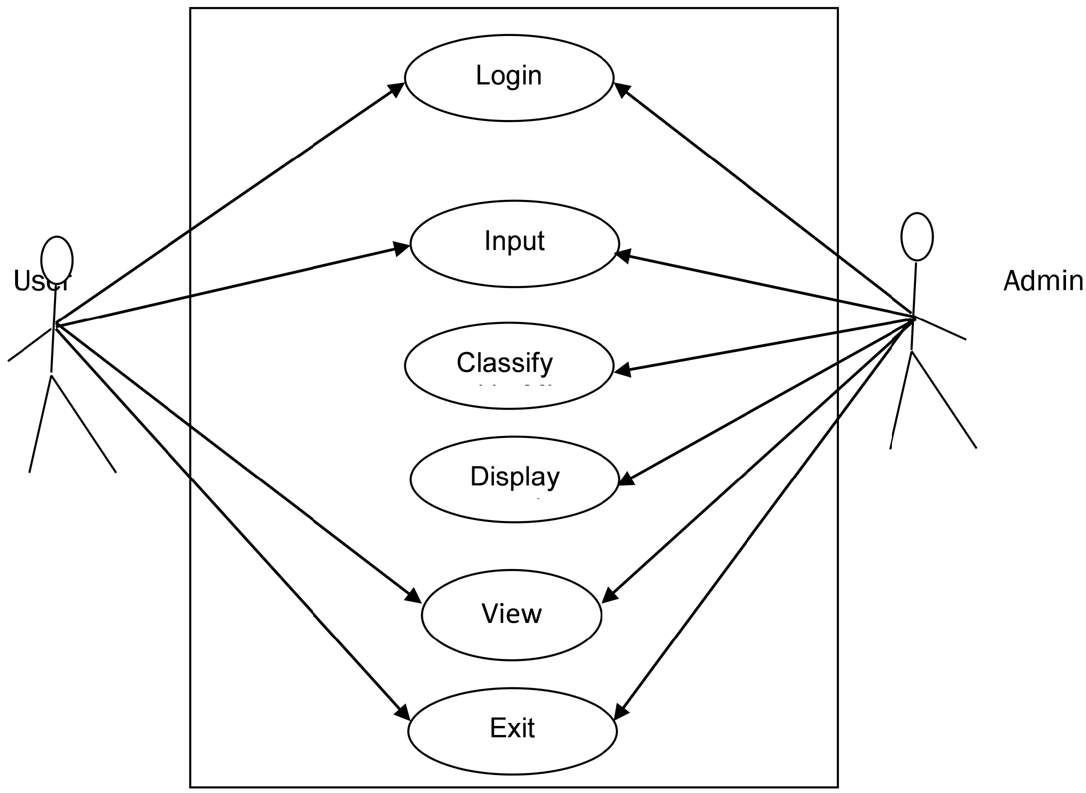

Figure 3.1: Use Case Diagram for Postpartum Depression

3.1 Dataflow Diagram

The dataflow diagram (Figure 3.2) represents the flow of data within a process or system, typically an information system. The DFD additionally gives details about each entity's inputs and outputs as well as the process itself. The training datasets were divided into test data and training data in the dataflow diagram in order to train and test the Machine Learning algorithm (ANN). A fresh input was provided into the machine program at run time to anticipate the dependent variable and produce the projected output.

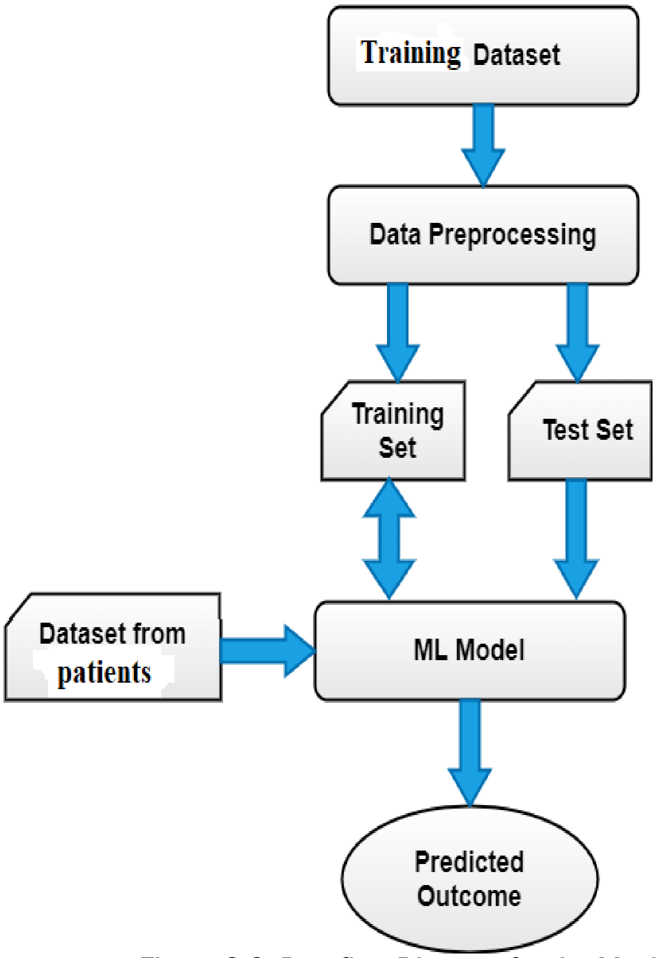

Figure 3.2: Dataflow Diagram for the Machine Learning application.

3.2 Postpartum Database

A database was created to carry the validated symptoms dataset gotten from the human expert at the hospital. Microsoft Excel was used to create a very simplified database for the symptoms which interacted with Python without any hassle. Figure 4.1 shows a screenshot of the database created carrying decoded symptoms assigned to binary codes as understood by the neural network

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	aa	bb	cc	dd	ee	ff	gg	hh	ii	jj	remark			
2	1	1	0	0	0	0	1	1	0	0	BABY BLUE			
3	0	0	0	1	0	0	1	0	0	0	OBSESSIVE COMPULSIVE DISORDER			
4	1	1	1	1	1	1	1	1	0	0	POST PARTUM DEPRESSION			
5	0	0	1	0	0	0	1	1	0	0	POST PARTUM STRESS DISORDER			
6	0	0	0	1	0	1	0	1	1	1	PSYCHOSIS			
7	1	1	0	0	0	0	1	1	0	0	BABY BLUE			
8	0	0	0	1	0	0	1	0	0	0	OBSESSIVE COMPULSIVE DISORDER			
9	1	1	1	1	1	1	1	1	0	0	POST PARTUM DEPRESSION			
10	0	0	1	0	0	0	1	1	0	0	POST PARTUM STRESS DISORDER			
11	0	0	0	1	0	1	0	1	1	1	PSYCHOSIS			
12	1	1	0	0	0	0	1	1	0	0	BABY BLUE			
13	0	0	0	1	0	0	1	0	0	0	OBSESSIVE COMPULSIVE DISORDER			
14	1	1	1	1	1	1	1	1	0	0	POST PARTUM DEPRESSION			
15	0	0	1	0	0	0	1	1	0	0	POST PARTUM STRESS DISORDER			
16	0	0	0	1	0	1	0	1	1	1	PSYCHOSIS			
17	1	1	0	0	0	0	1	1	0	0	BABY BLUE			
18	0	0	0	1	0	0	1	0	0	0	OBSESSIVE COMPULSIVE DISORDER			
19	1	1	1	1	1	1	1	1	0	0	POST PARTUM DEPRESSION			
20	0	0	1	0	0	0	1	1	0	0	POST PARTUM STRESS DISORDER			
21	0	0	0	1	0	1	0	1	1	1	PSYCHOSIS			
22	1	1	0	0	0	0	1	1	0	0	BABY BLUE			

Figure 3.3 Database for the Symptoms of Postpartum Depression Categories

4. PROGRAM DESIGN

The procedures a programmer takes before beginning to code the program in a particular language are called program design. When these procedures are implemented, the finished software will be simpler for future programmers to maintain. Three main areas of action are as follows:

Understanding the Program: Understanding the purpose of a program usually involves understanding its Inputs, Processing and Outputs. The input for this study were generated from interview conducted by a Psychiatric doctor after observing/interviewing the patients. The said input were processed with a Machine Learning classification algorithm (ANN) to automatically generate the desired output without human intervention. The input is the independent variable while the output generated is the dependent variable.

Using Design Tools to Create a Model: In this study, we classified postpartum depression using a model built on an artificial neural network (ANN). One of the machine learning classification methods is the ANN.

Develop Test Data: In this investigation, we employed two different types of data, namely the 1500 records from the training datasets of independent and independent variables. Test data (25%) and training data (75%) were separated from the training datasets. A fresh set of test data was fed into the model for prediction after it had finished training. The test data utilized for prediction demonstrated the model's effectiveness.

Using Design Tools to Create a Model: We used the Use Case as a tool to explain the functionality of the system. It showed the role of the actors (user and administrator) their functions in testing and implementation of the system.

4.1 Dataset Employed

Standard datasets are used to gauge the prediction system's performance and assess how accurate it is. The following two standardized sources provided the dataset that was utilized in this work to train and evaluate the ML algorithm:

i. **Kaggle datasets**: they are reliable open-sourced datasets from well recognized data science and artificial intelligence platform acquired by Google in March, 2017. In this study a total 1,500 postpartum depression datasets was obtained and used in analyzing the performance ability of the machine learning algorithms. This also informed as our choice of algorithms because ANN seemed to have out-performed the others using the datasets

ii. **Clinical symptoms:** these set of datasets consist the informed symptoms of PPD as obtained from the clinician at Federal Neuro-psychiatric hospital, Uselu, Benin city. They were the datasets used in training and testing the system for performance.

To code in the environment, from the menu click on new, select python 3 ipykernel. The application for postpartum depression was coded.

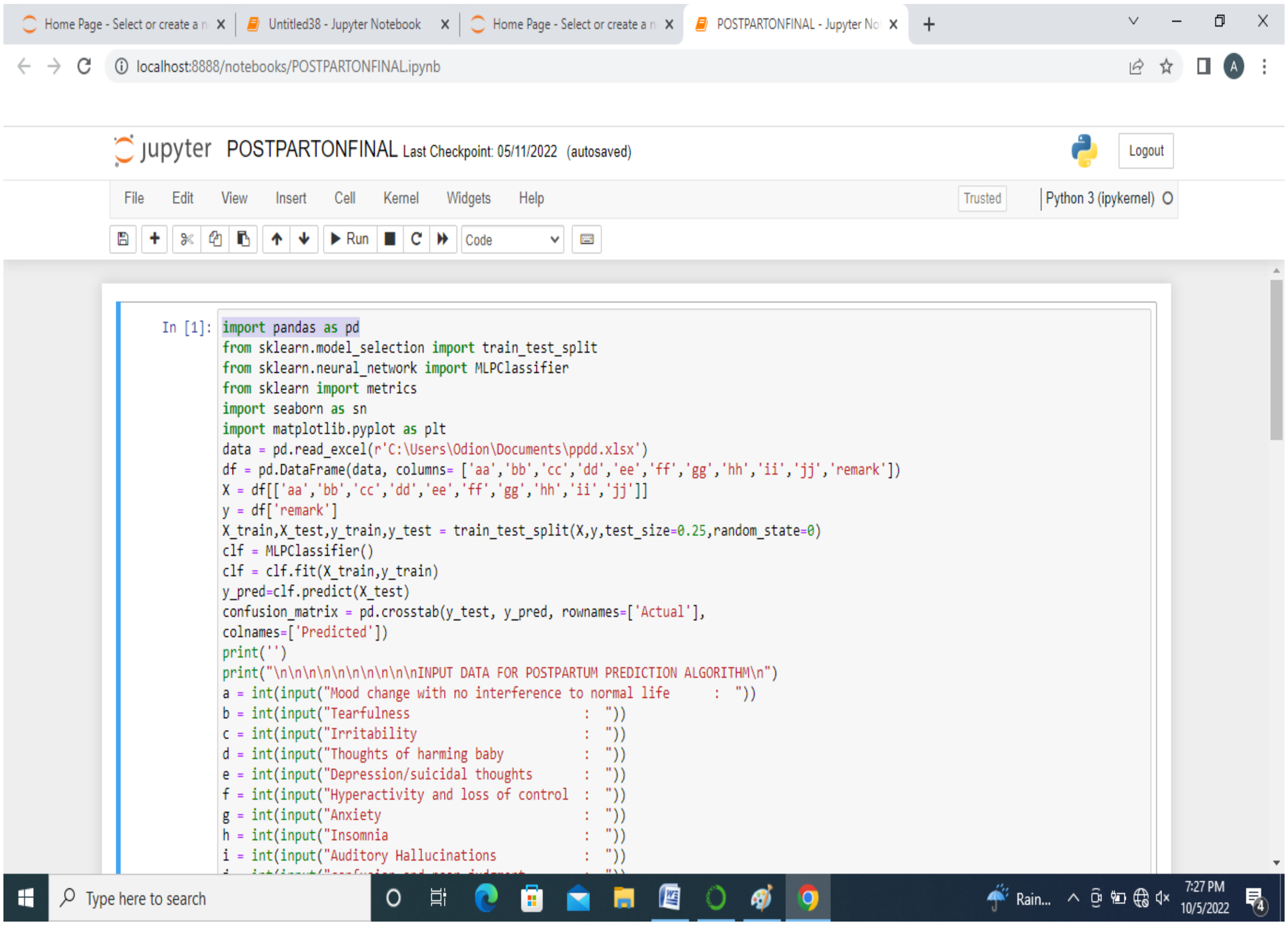

Figure 4.1: Python program for postpartum depression.

The screen short in Figure 4.1 represents the python codes for the Machine Learning application for postpartum depression.

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Step iv.Test run of the Machine Learning application

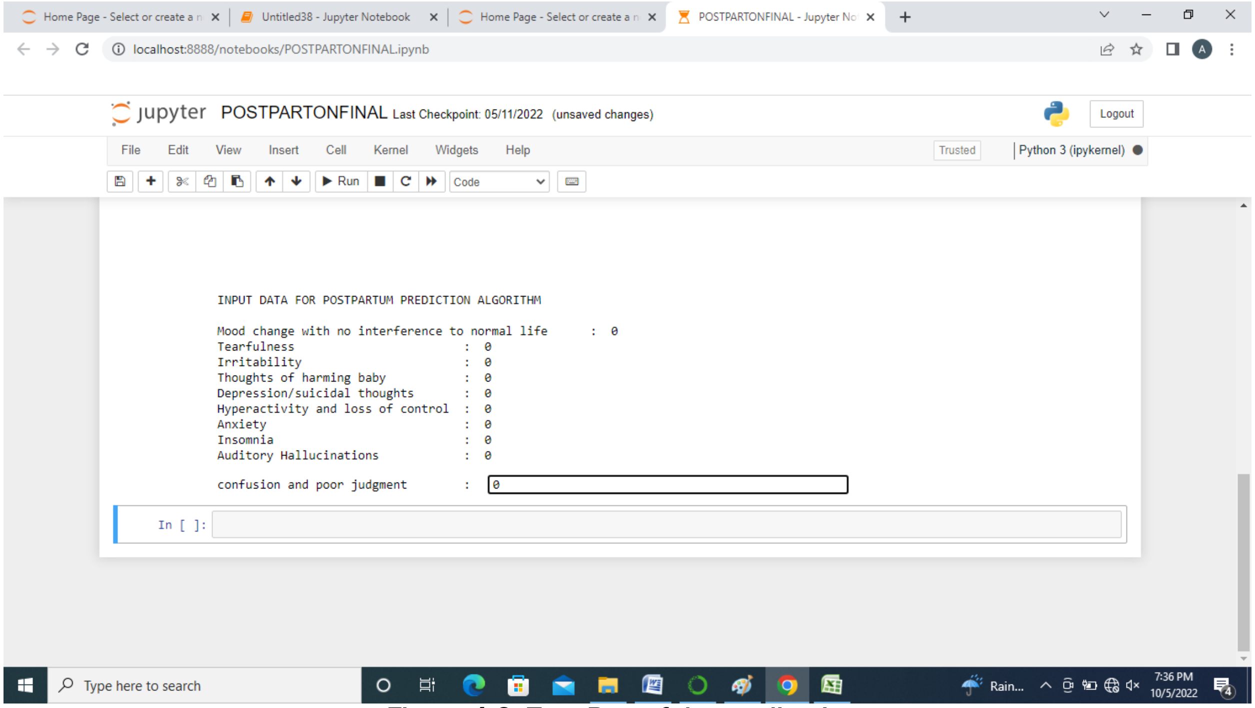

Figure 4.2: Test Run of the application

A user interface was displayed when the run program was launched, allowing the user to enter the indications and symptoms collected from patients as illustrated in fig. 4.9. Then, using a patient who did not exhibit postpartum depression as an example, we entered a set of data. The absence of the patient's symptoms and indicators is represented by the number "0" next to them. Confusion and poor judgment were input as the final symptom, and the ANN classifier instantly created the independent variable, algorithm accuracy, and seabone (the graphical test data for algorithm training).

5. SUMMARY

The study aimed at implementing a system for the diagnosis of postpartum depression while following aforementioned objectives sequentially. Diagnosis is a very important aspect in health care. It entails both the process of examination and decision related to prognosis and interventions. A sizable body of empirical research has shown that human intuitive judgment and decision-making are frequently far from ideal, and that they become significantly worse in conditions of complexity and stress. Human beings depend on doctors making accurate judgements in clinical diagnosis. In this study, the use of neural networks in the diagnosis of PPD was examined using data sets from Kaggle and symptoms reported by human experts (both online and offline), respectively. The findings demonstrated that the created model could reasonably predict whether a patient had PPD or not based on age, hunger, mental state (such as melancholy, irritability, anxiety, tearfulness, etc.), suicide thoughts, eating and sleeping pattern, and difficulty connecting with the baby. Although the results from the created model are generally encouraging, further study and analysis are required to fully comprehend the relationship between other significant characteristics that are also indicators of PPD. Future research can incorporate input factors like parity and illness duration to boost model performance.

5.1 Recommendations

The following recommendations were made from the findings of the study:

1. There should be an increased awareness on mental health illnesses that affect nursing mothers or pregnant women.
2. Due to the simplicity of the required psychosocial information encoding utilized in this study, it will enable a suspected post-partum depressed person easy access to give required information for the designed system to effectively detect depression.
3. Improved diagnosis through symptoms specification.
4. Development of complete applications for diagnoses and treatment of postpartum depression that can be used in today's widely used devices

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