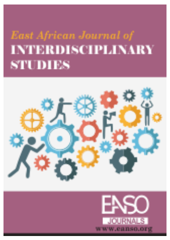

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Original Article

User Embedding Long Short-Term Model Based Fecundity Prediction Model Using Proposed Fecundity Dataset

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Fecundity, Fecundity Prediction, Long-Short-Term Model, Deep Learning Pregnancy Prediction, Health Tracking Mobile App, Subfertility, Pregnancy.

ABSTRACT

Fecundity prediction is a process that helps couples to understand their fertility status. Fecundity prediction as a domain could be supported by developed intelligent models using a computational method and fecundity data. Although fecundity data and models have been proposed, the problem of low data size and dimensionality of the proposed fecundity dataset has been identified due to the data collection approaches used and the problem of using a weak subfertility definition in the development of a User-embedding LSTM-based fecundity prediction model. To solve the identified problems, this study proposed a fecundity dataset by adopting a hybrid data collection approach using the strengths and disregarding the setbacks of existing data collection approaches and then proposed an improved User-embedding LSTM-based fecundity prediction model based on an improved subfertility definition. A large size fecundity dataset was generated and used for the implementation and evaluation of the existing and proposed LSTM-based fecundity prediction models and the proposed model generated better AUC-ROC evaluation results.

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INTRODUCTION

The term fecundity in the health care domain is used to describe the capability of achieving pregnancy by couples (Greil, 1997). Fecundity prediction is a process that involves determining the pregnancy probability. Predicting fecundity means understanding the biological and fertilisation heterogeneities relating to getting pregnant and this could help determine the fertility status of women early enough to enable quick awareness and treatment of infertility if noticed (Greil, 1997). The traditional approach used to carry out fecundity prediction tasks involves an interaction between the specialists (gynaecologists) and the couples; this approach is however, less efficient due to the ratio of specialists to patients especially when the patients population is high (Scarpa and Dunson, 2007), more so, the fecundity prediction analysis report by specialists are memory-based, which cannot be appraised (Symul *et al*., 2018) and thus might cause the specialist to be bias during rendering of fecundity prediction care to the couples (Gianfrancesco *et al*., 2018). Prediction of fecundity is a fundamental problem in women's health care and attempts have been made to help resolve this problem using data mining techniques (Dunson, 2001; Lum *et al.*, 2016).

Data mining methodology is a multidisciplinary domain of computing which uses knowledge acquired from these disciplines to discover useful patterns from specific domain data that are applicable to the domain (Jiawei and Kamber, 2001). Methods like the Bayesian method (Dunson, 2001; Dunson and Stanford, 2005; Scarpa and Dunson, 2007; Lum *et al.*, 2016), Long short-term model (LSTM) (also known as Recurrent neural network) method (Liu *et al.*, 2019) and Markov chain methods (Pennoni *et al.*, 2017 and Symul *et al.*, 2018) have been applied to help solve fecundity prediction problem. Fecundity prediction models have been discovered to help understand influencing factors of women's conception chance.

The models used for modelling fecundity prediction are categorised into Time to Pregnancy models (TTP), Barratt and Marshall (1969) and Schwartz *et al.* (1980) models (BMS), Extension of TTP (ETTP) and Deep Learning for Pregnancy prediction (DLPP) (Ecochard 2006; Liu et al. 2019). However, proposed models that fall under the category of TTP, like Ecochard and Clayton (2000) or ETTP like Dunson and Colombo (2003) and McDonald et al. (2011) or BMS like Colombo *et al.* (2006) were developed using statistical distributions and the assumption that pregnancy is achieved independently within a cycle. DLPP models like LSTM extension of BMS (LSTM-BMS) and LSTM extension of TTP (LSTM-TTP) (Liu et al., 2019) also used such an assumption. The implication of such an assumption to their proposed models is that the models learn every cycle within the fecundity dataset as a couple of cycles and thus every couple is assumed to be fertile, but this assumption is not always the case. Although this study proposed fecundity prediction model that used the DLPP modelling approach due to its scalability advantage

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over the other categories of modelling fecundity prediction, an improved assumption relating to pregnancy achievement with respect to menstrual cycles proposed by Liu et al. (2019) during the development of a user embedding LSTM (LSTMUE) was used.

LSTMUE of DLPP was proposed using LSTM and the assumption that, irrespective of the fact that pregnancy is achieved within a cycle, it should be noted that pregnancy achieved in the current cycle is dependent on the efforts to get pregnant in previous cycles (for subfertile couples). Liu et al. (2019) LSTMUE of DLPP models was observed by this study to be one of the most recent models for modelling fecundity prediction. However, Liu et al. (2019) assumption defined subfertility with the restriction that it can only occur within seven cycles (that is, the current menstrual cycle in which pregnancy is achieved is dependent on the previous 7 menstrual cycles). This subfertility assumption is weak because couples are said to be clinically infertile only after one (1) year; therefore, subfertility can occur within 12 cycles (Van der Steeg *et al.,* 2007). Based on the weak subfertility assumption used in existing LSTMUE, this study improved the existing LSTMUE by improving the subfertility assumption using 12 cycles.

Furthermore, the data used in implementing and evaluating fecundity prediction models in previous works have been records of the fertilisation process and cycle viability factors within the women's menstrual cycles over a period of at least 12 months (Scarpa and Dunson, 2007; Lum *et al.*, 2016). However, analysing the fertilisation factors with respect to pregnancy is considered with higher priority in most research in fecundity prediction using data mining due to the fact that the fertilisation process is the key to getting a woman pregnant (Ecochard, 2006). The challenge of how to collect high-quality and sufficient quantity data is categorised into medical studies and Health Tracking Mobile App (HTMA) approaches (Liu *et al.*, 2019; Smarr *et al.,* 2017).

Medical studies and Health Tracking Mobile Apps (HTMA) have been the approaches for the collection of data for solving the problem of fecundity prediction (Liu *et al.*, 2019), but both approaches were observed with challenges. Data collection using Medical (Fecundity) studies is the earlier method employed during fecundity prediction model development. However, it provides sufficient dataset dimensionalities but considers a lower couple population and generates a low quantity of the datasets (Smarr *et al.*, 2017; Gianfrancesco *et al*., 2018; Liu *et al*., 2019). By implication, proposed fecundity prediction models implemented using medical studies data give inferences that may be applicable to a lesser population, and the scalability of the proposed fecundity prediction models is not adequately tested. Researchers like Colombo and Masaratt (2000) and Colombo et al. (2006) used this approach.

On the other hand, the use of HTMA data (Clue and Natural Cycles dataset) gives the opportunity of having a broader application of the fecundity prediction model due to the larger size of HTMA data used. Nevertheless, HTMA data is also faulty due to its reduced dimensionality caused by the presence of high missing values and less predicting useful features of pregnancy (Liu *et al.*, 2019). Researchers like Scherwitzl *et al*. (2016) and Liu et al. (2019) published the dataset collected using this approach.

In the domain of Fecundity prediction, this study improved an existing DLPP model (LSTMUE) that uses the knowledge gained from sufficient historical and current fecundity detail of couples to predict the fecundity of other couples with no knowledge of their fecundity status. Also, a new fecundity dataset is proposed containing a reasonably large size of daily fecundity data for others and this study's proposed fecundity prediction model evaluation and further descriptive analysis of fecundity.

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MATERIAL AND METHOD

In this research, the fecundity prediction model is proposed focusing on how the coital occurrence pattern influences fecundity prediction. Also, a fecundity dataset is proposed and used for evaluating the proposed model. *Figure 1* illustrates the framework used for achieving the objectives of this study.

Figure 1: Framework for fecundity predictive model development

Phase 1: Data Collection
• Problem domain knowledge acquisition • Collection of data
Phase 2: Fecundity prediction Model Development
• Creation of extended LSTMUE model for fecundity prediction data analysis • Implementation and Evaluation of extended LSTMUE based fecundity prediction model • Comparison of proposed model with existing model.

Research Framework

Phase 1: Data Collection

Data collection plays an important role in discovering artificial intelligence solutions to healthcare problems. The use of Medical studies and HTMA data have its setbacks. And approaches of data collection like approaches involving health care experts (Stead, 2018) and collection of data outside the health care system (clinics and hospitals) (Madox *et al.*, 2019) were advised to be adopted during data collection phase of discovering intelligent solutions to health care problems. Based on this, a hybrid data collection approach is introduced in this study. The medical studies approach is observed to lack the problem of low dimensionality due to its well-defined features used and supervision of participants' entry, while the HTMA data collection approach lacks the problem of data size due to convenience experienced by participants when entering their respective data based on the fact that an internet-based data collection platform is used. Based on the advantages of both medical studies and HTMA approaches, this study adopts a data collection approach using both advantages.

DeJonckheere *et al.* (2019) adopted such data collection approach for the collection of data relating to weight gained in youth during pregnancy and it was observed that the approach was good in collecting a significantly large amount of data due to the accessibility of its tools. The approach used is a combination of 3 data collection tools; text messaging, social media, and interviews. The combination of the 3 data collection tools gives a substantial dataset size due to the access of text messaging and social media tools to a larger population and clarification of details due to the interview tool. Although the approach is adopted for the collection of data containing youth perspectives concerning weight gain during pregnancy, it was not used for the collection of data within this study problem domain. *Figure 2* depicts the conceptual framework of this study's data collection approach. This study data collection framework is an adjusted DeJonckheere *et al.* (2019) data collection framework.

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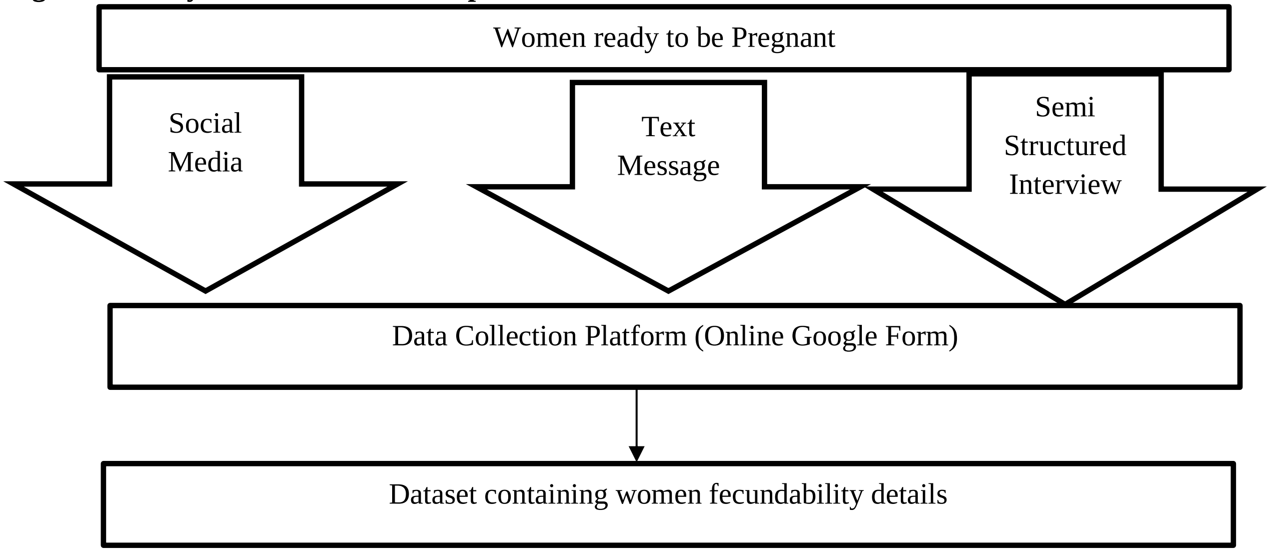
Figure 2: Study data collection conceptual framework



Problem Domain Knowledge Acquisition

To enable quality data collection from a problem domain, acquiring knowledge about the problem is very important. This process involves understanding the problems involved in the fecundity prediction task. However, based on the discovered problem of low dimensionalities involved in HTMA datasets, this study identified the relevant dimensionalities involved within the problem domain so as not to pose the low dimensionalities limitation on this study dataset. The dimensionalities of the fecundity prediction task are the factors to consider when carrying out fecundity prediction and based on these factors, the features of this study's proposed dataset are generated and the features values will be the possible outcomes of the respective factors.

For instance, factors A and B were discovered as dimensionalities of the fecundity prediction task then features A and B will be the replacement of factors A and B, respectively. If factor A has possible outcomes of a, a1 and a2, then such outcomes will be used as the feature values for feature A within the proposed dataset.

However, based on the contribution of Stead (2018), where it was said that research on the application of artificial intelligence in the healthcare domain should involve the respective healthcare experts, identification of dimensionalities process will be carried out with the help of pregnancy care experts through a series of interviews. To achieve the dimensionalities identification task, the following processes are carried out.

1. Visits to health care centres for pregnancy care experts' identification and appointment scheduling
2. Visits to health care centres for dimensionalities and pregnancy stakeholders' identification. During this process, the following question will be asked.
    - What are the factors to consider when predicting fecundity?
    - What are the possible outcomes of each factor identified in (a)?
    - Who are the stakeholders in predicting pregnancy?

Based on the bias data sampling limitation affecting data collected using medical studies, this study ensured the collection of data samples is not biased by carrying out data sampling in every location

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where pregnancy care is carried out within Lokoja, Kogi state. The major locations for not only pregnancy care but health care are the Hospitals/Clinics and Herbal Medicine centres; therefore, several Hospitals/Clinics and Herbal medicine centres within Kogi state will be used as case studies.

Collection of Data

Preparation of data collection platform

Before the collection of data, a data collection platform was developed so as to ease the collection process. Features of the proposed dataset were represented as the factors identified during the dimensionalities identification process in the problem domain knowledge acquisition phase. Women's inputs were collected based on the features and inputs were made based on factors possible outcomes. To prepare the data collection platform, an online Google form was created with the identified fecundity prediction factors as the fields to be inputted by users. Online Google form is an easy-to-use data entry template that gives the opportunity to administrator to download all entries through the form in one .csv database file. To enable the users to have access to the online Google form, the URL of the online Google form was distributed to them via text messaging and social media (WhatsApp and Facebook).

Data collection using the prepared data collection platform

To complete the process, two (2) sub-processes were carried out.

1. Visit to health care centres for pregnancy stakeholders' enlightenment on current research significance and a demographic survey (collection of contact detail (active phone number, Facebook/WhatsApp account detail)). For online enlightenment, text containing the enlightenment along with the online Google form link was created and posted to social media chat groups and individual contact details were collected. Enlighten the pregnancy stakeholders on the significance of this study might come as an encouragement for those stakeholders with negative mindsets on the study. As part of the encouragement, some stakeholders were incentivised. Also, the following inclusion criteria into the study was mentioned;
    - Women participants have to be married or in a serious relationship.
    - Women participants must have the intention of getting pregnant with a partner, thus no usage of contraceptives during the study.
    - Women or their respective partners must be free of any fertility problems or any illness that could hinder pregnancy achievement. Also, for candidates to be eligible, they were not supposed to be on any infertility medications.
2. Send data collection platform to pregnancy stakeholders and receive pregnancy stakeholders' responses. To send the data collection platform, the URL of the online Google form was distributed to the details in the demographic survey. And the medium for distribution were via text message and social media (Facebook and WhatsApp). Data collection via text message survey was adopted due to the fact that the approach was the most preferred mode of data collection among low-income communities (Chang *et al.*, 2014; Sharp *et al.*, 2014) and very suitable for real-time (immediate feedback) data collection (DeJonckheere *et al.*, 2019). Data collection via social media survey is now an approach with growing interest due to its frequent visits by internet users and can be used to understand its users based on their comments and posts (Falzone *et al.*, 2017). Based on the idea that

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most Herbal medicine centre patients and some Hospital/Clinic patients might be uneducated on mobile phone usage, a one-on-one set of interviews was necessary for the collection of data. The interview data collection approach is known for its efficacy in the detail clarification process (DeJonckheere *et al.*, 2017).

Apart from the Online Google form, a paper questionnaire was also produced for a set of women with no access to the internet. The data collection platforms (both paper questionnaire and Google form) were reviewed by fertility experts interviewed. Furthermore, to ease the process of distribution and collection of survey responses and paper questionnaire responses, two students of the Computer Science Department at Federal University Lokoja were involved in the study. Additionally, in each medical centre, personnel were enrolled in the process.

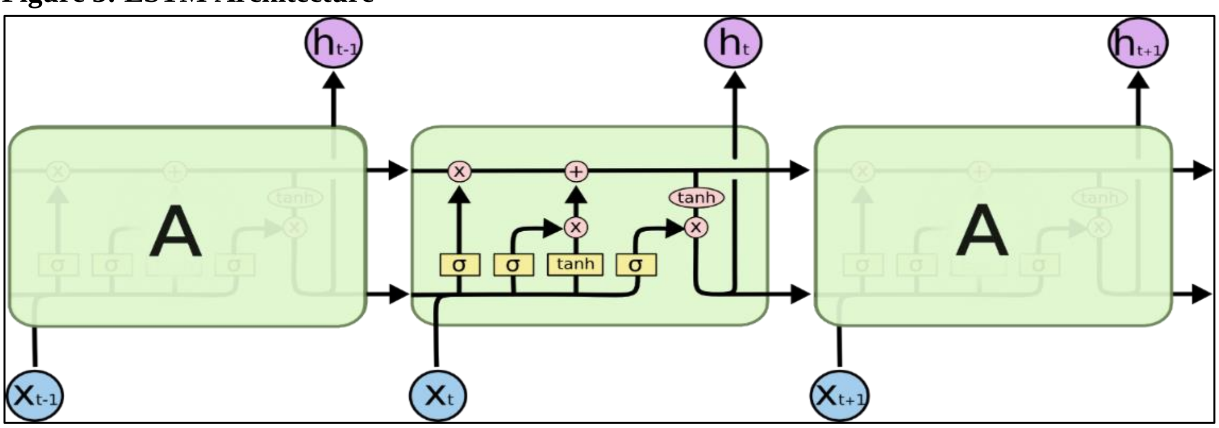
Phase 2: Fecundity Prediction Model Development

The purpose of this phase was to analyse the data collected using the proposed and existing LSTMUE model so as to evaluate both models and thus discover the better-performing fecundity prediction model.

Creation of the Proposed LSTMUE Model for Fecundity Prediction Data Analysis

It is observed that fecundity datasets are highly randomised in nature and are sampled in measurement in time and that to best analyse randomised and time series data, an LSTM Deep learning model is used (Liu *et al.*, 2019). LSTM is a recurrent neural network method which forms a cyclic connection between units (input; set of features entries $\{X_{t-1}, X_t, X_{t+1}\}$, hidden; set of outputs $\{h_{t-1}, h_t, h_{t+1}\}$ relating to the operations in the cell states {A}, and output; predictions) of a neural network, see *Figure 3*. The hidden state at each time step maintained by the model can be used for prediction. The strength of LSTM falls on the operations within the cell states. Also, the feature of storing dependencies and then concatenating with current states for predicting future states. *Figure 3* shows the architecture of the LSTM model. See Olah (2015) for a detailed understanding of LSTM networks.

Figure 3: LSTM Architecture



Considering the assumption of subfertility in the creation of an LSTM-based fecundity prediction model, Liu et al. (2019) proposed an LSTMUE, as described in *Figure 4* architecture. The LSTMUE has double hidden state layers which contain an LSTM each. The first LSTM is fed with six (6) cycles' (that is H = 180 days) daily user entries, which serve as a couple's history of the process of getting pregnant. The final state of the first LSTM serves as the user embedding vector which was fed

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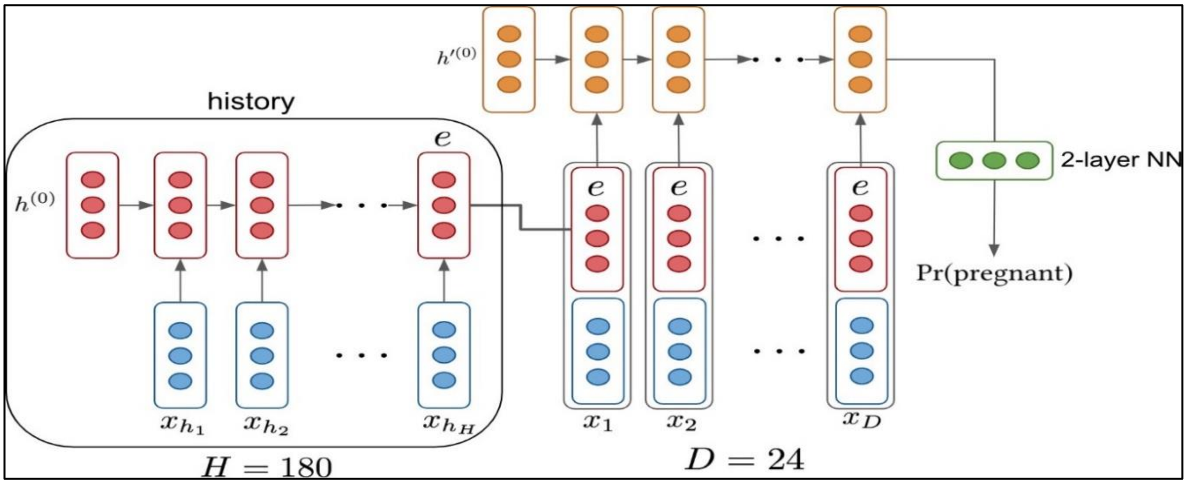
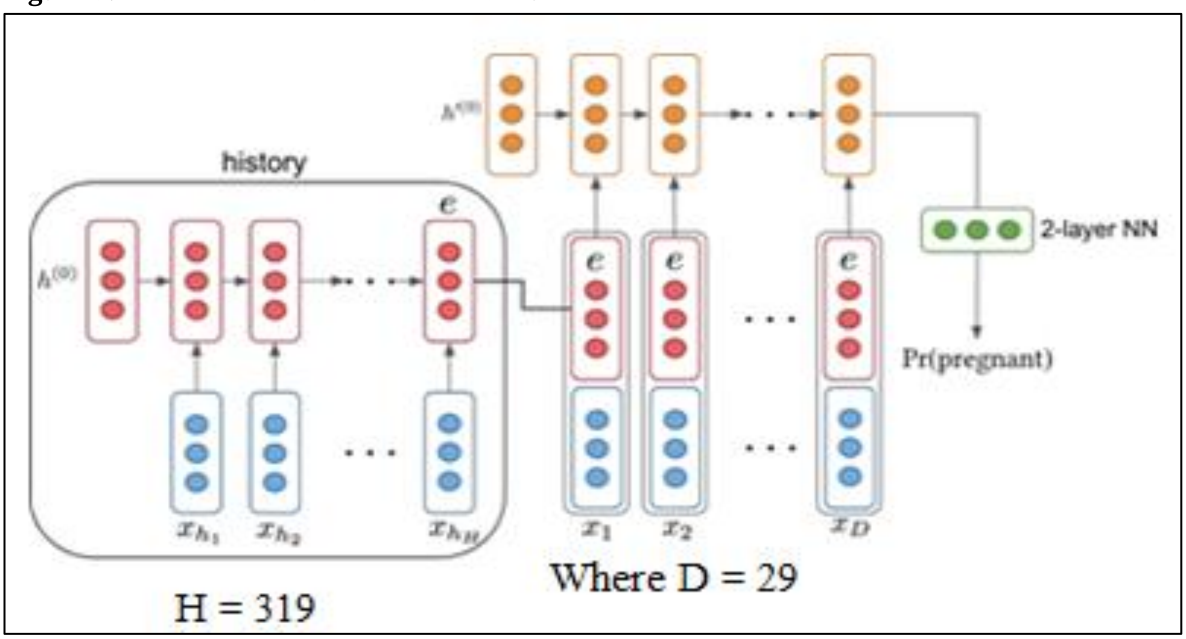
along with the current cycle (that is D = 29) user daily entries to the second LSTM. The value for D = 29 was D = 24 in Liu et al. (2019) study. This was the study's decisive value based on the fact that achieving pregnancy above the 24th day of a menstrual cycle is very unlikely. However, this study decided not to make such a restriction.

Figure 4: LSTMUE Architecture



The LSTMUE model adapted to estimating pregnancy probability considering 6 cycles; however, since subfertility ends at a 12 cycles benchmark, this study extends the LSTMUE learning architecture to accommodate learning from 12 cycles, as described in *Figure 5*.

Figure 5: Extension of LSTMUE architecture



The history (left) segment of the architecture represents historical details of couples trying to get pregnant across 11 cycles. The daily entries *x* across D (from x_1 to x_{29} days across a cycle) are learnt by concatenating *x* and the output of the operations of the cell state to derive a hidden feature xh_1, and then

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xh_1 is fed to the next input state. This learning process continues until the couples' entries in the last day (H = 348) of the the12th cycle are learnt. However, since the essence of considering modelling fecundity prediction with more cycles was to improve the performance of the proposed fecundity prediction model, excluding adapting to the pregnancy achievement condition for subfertile couples, both the LSTMUE and the improved LSTMUE were evaluated to identify the better-performing fecundity prediction model.

Implementation and Evaluation of Extended LSTMUE-Based Fecundity Prediction Model

Before the application of any data analytics to the dataset sampled from the field, a certain data preparative process is usually carried out to enhance the results of the analysis. Fecundity prediction data collected during the data collection phase contained tuples of women's cycles where pregnancies were observed and cycles where no pregnancies were observed. Although, women filling out the data collection platform were advised to either fill out the form every day (if convenient) or most importantly the days when intercourses were observed and pregnancies were also observed. To reduce irrelevant tuples from the data collected, tuples of cycles that had little or no relevance to the process of getting pregnant was removed manually based on the knowledge acquired during the knowledge acquisition process in phase 1. Using Python programming language, models were implemented and evaluated.

The evaluation measures used for evaluating the proposed fecundity prediction model was based on Area Under the Curve - Receiver Operating Characteristics (AUC - ROC) curve since it has been a standard for evaluating DLPP (Liu et al., 2019). AUC - ROC curve is a metric that helps measure the performance of a classifier. In as much as it can be used for multiple classes' classifiers, it is best used for binary classes classifiers. It is a better classifier evaluator than the accuracy estimator due to its unbiased nature caused by test and training dataset size.

In a dataset where two classes (positive or negative) are observed, a classifier sensitivity is a rate at which the classifier classifies tuples as positive and are actually positive. This is also known as True Positive Rate (TPR). On the other hand, the rate of tuples classified by the classifier as negative but are actually positive are also known as False Positive Rate (FPR). The formula for TPR and FPR are given in equations (2) and (3), respectively. Where *TP* is the number of tuples classified as positive and are positive, *FP* is the number of tuples that are classified as positive but are negative, *TN* is the number of tuples that are negatively classified and are negative, and tuples number that are negatively classified but is actually positive is denoted by *FN*.

$$TPR = \frac{TP}{TP+FN} \quad (2)$$

$$FPR = \frac{FP}{TN+FP} \quad (3)$$

The probability curve that plots TPR with FPR so as to distinguish the signal from the noise is the ROC, while the AUC summarises the ROC curve and measures the ability of the classifier to distinguish between the classes. The fecundity prediction model helps to distinguish between women who are capable of getting pregnant or not; thus, AUC-ROC helps estimates the model's ability to carry out the task at hand. Conclusions were drawn from the comparison of both LSTMUE and this study proposed extended LSTMUE-based fecundity prediction models AUC-ROC evaluation results.

RESULTS

Knowledge Acquisition

Based on this study framework, the ideas necessary for carrying out the fecundity prediction task were acquired through frequent interviews with experts (Dr. Adewole Adebayo of Federal Medical Center, Lokoja, Dr. Ohi, Ohioze and Colleague Dr. Idris of Confluence City Hospital, Lokoja, all in Kogi State,

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Nigeria). Based on their collective views, identifying factors used for analysing women's fecundity depends on what aspect of fecundity was to be analysed. For instance, when analysing the fecundity of women (especially healthy and young women) with respect to timing intercourse to achieve pregnancy, frequency of intercourse occurrence is considered, and basal body temperature with respect to the ovulation period is also considered. Also, when considering the fecundity of healthy women that have delays in achieving pregnancy, age could sometime be a factor for such delay. Using such knowledge, the factors of Intercourse occurrence, Basal body temperature and age were extracted as factors to be considered for fecundity analysis.

Also, working in parallel with knowledge acquired from experts was knowledge acquired from previous research. Moreover, the knowledge acquisition step was a continuous process until the aim of this study was achieved. This study was proposed to and approved by the department of Computer science, School of Information and Communication Technology, the Federal University of Technology Minna, Nigeria.

This study collected over 40 factors that could be used for fecundity prediction. These factors are a combination of factors extracted from experts' interviews and previous research on the fecundity prediction model. However, *Table 1* describes the selected factors (from the overall factors collected) used for data collection from participants. The factors selected were based on the selection of previous fecundity data collection studies (Colombo and Masarotto, 2000); this is due to the usage of the study dataset by a high number of researchers focusing on analysing fecundity.

Table 1: Factors for fecundity measurement

No	Factors Name	Factor Description	Factor Type
1	Age	Current age of women and their respective partners	Integer
2	Previous Pregnancy	The amount of pregnancy (resulting in deliverance or miscarriage) experienced before participating in the study	Integer
3	Last Delivery	When was your last delivery?	Integer
4	Last Period of Breast Feeding	When was the last time (in months/years) you breastfed an infant?	Integer
5	Last Period of Pregnancy	When was the last time (in months/years) you experienced pregnancy	Integer
6	Marriage Period	How long have you been married?	Integer
7	Nature of Exercise	What type of exercise do you partake in?	Ordinal
8	Stress Nature Caused by Job	How stressful is your job?	Ordinal
9	Alcohol Intake	How frequently do you take alcohol	Ordinal
10	Menstrual Cycle Length	How many days was your last cycle	Integer
11	Menses Start Period	What day in your last cycle did your menses start	Integer
12	Menses Period Length	How long did your menses last	Integer
13	Daily Body Feeling	Daily record of how you feel, be it emotionally or medically.	Time Series
14	Daily Basal Body Temperature	Daily record of increase in temperature during ovulation	Time Series
15	Daily Intercourse Occurrence	Daily record of intercourse experience with a partner	Time Series
16	Daily Pregnancy Status	Daily record of pregnancy test result	Time Series

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Data Collection

The Hospitals/Clinics visited for the demographic survey and the distribution of paper questionnaires are shown in *Table 2*. Over 1145 demographic details were collected, 907 paper questionnaires were distributed and the Online Google platform link were sent to several social media chat groups. A Facebook page named Fecundity Study was created and the page link was sent to other social media chat groups. *Table 2* shows the distribution of the demography survey and paper questionnaire to the medical centres visited.

Table 2: Distribution of Demographic survey and questionnaire to Medical Centers

Medical Center	Number of Demographic Survey Distributed	Number of Questionnaire Distributed	Number of Participants Who Responded
Federal Medical Center Lokoja	320	290	197
Specialist Hospital Lokoja	233	206	147
Poly Hospital	143	101	89
Confluence City Hospital	278	209	199
Rehoboth Hospital	171	101	98

Dataset

Based on the structure of the collected factors to consider when predicting fecundity, a set of 2838 couples details were collected, that is, 730 through paper questionnaires and 2108 through online Google forms. This study was approved as part of a Doctor of Philosophy (PhD) study in the department of Computer Science, School of Postgraduate Studies, Federal University of Technology Minna, and as such the fecundity dataset and other data generated from the study could be verified as addressed. For further address details, the school website (www.futminna.edu.ng) can be visited. Furthermore, the dataset could be accessed on request from this paper's corresponding/main author.

For each woman, the details collected were categorised into a one-time detail entry constituting factors 1 to 9, as shown in *Table 1*, and a daily or monthly detail entry constituting factors 10 to 12 (for monthly) and 13 to 16 (for daily). Participant response to questions from factor 1 to 9 was made one time throughout the study, while responses to questions from factor 13 to 16 were made daily or most importantly, the day intercourse was experienced, and this is due to the fact that intercourse is the key factor that must be achieved to achieve pregnancy. The responses to the daily questions were combined until pregnancy in the menstrual cycle was observed, then a record was created for the respective participant combined with both the monthly response to the questions from factor 10 to 12 and the one-time response to the questions from factor 1 to 9. Every record in the dataset was a combination of responses to questions from factors 1 to 16 collected within a participant's menstrual cycle.

To help participants identify the beginning of a menstrual cycle, it was noted that the end of the menses experience begins a menstrual cycle, while a day to the end of the menses experience ends the menstrual cycle. However, a participant is expected to respond to the questions from the day the entry starts to the day pregnancy is observed or to the end of 12 menstrual cycles. Predicting pregnancy is the purpose of the study, therefore responses that lead to pregnancy was the main focus of the study, although responses leading to no pregnancy was also collected so as to analyse the anomaly of the process of getting pregnant. Furthermore, why the participants needed to stop responding to the study

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questions was because it was observed medically that if after 12 menstrual cycles a couple tried to conceive but were unsuccessful, then the couple would be noted as clinically infertile. Based on this fact, it was concluded that if after responding to the questions for 12 cycles and pregnancy was not achieved then chemical factors will then be involved for pregnancy to be achieved, which is not the scope of this research. Based on the description of the dataset, 2838 participants' responses were collected, which in turn gives a total of 10191 menstrual cycles (tuples/records) collected from the fecundity study.

Extended LSTMUE-Based Fecundity Prediction Model Implementation and Evaluation

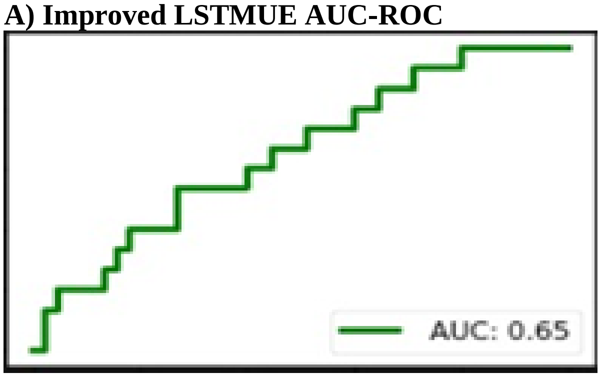
Before the implementation of the proposed model using the generated dataset, the non-informative tuples as described as follows, were ignored from the data collected:

- Intercourse episodes are key to pregnancy occurrence, thus making it a very important variable in determining pregnancy probability. By this, menstrual cycles resulting in either pregnancy or not without the occurrence of intercourse are not informative. Seventy-two participants' records were removed from the generated dataset due to such observed entries.
- The fertile period is known for the period of pregnancy; therefore, menstrual cycles that may result in pregnancy must have an occurrence of intercourse within its fertile period. Although the sperm of the male can survive in the reproductive tract of the female for at most three (3) days, of which within the three (3) days egg produced by the female can be fertilised to result in pregnancy. Based on these facts, menstrual cycles with intercourse occurrence outside the period from three (3) days before the cycle's fertile period to the end of the fertile period are less informative. Three hundred twenty-five participants were also observed to have entered the described records; hence the records were removed from the dataset.

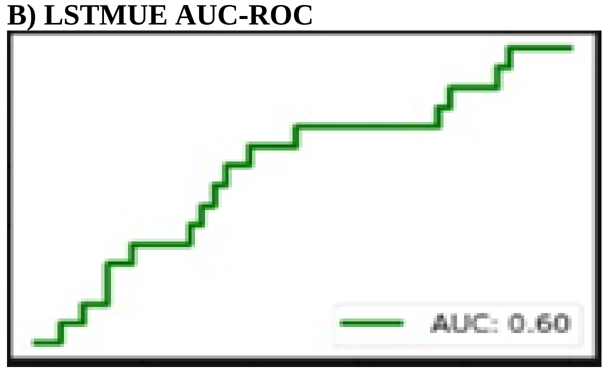
The focus of this study with respect to analysing fecundity is characterising the relation of coital patterns (intercourse) and pregnancy probability. Therefore, the mentioned features of the generated dataset features were selected. Also, in the proposed dataset, factor values were represented with alphabets (a, b and so on). LSTM technology works with numeric data, so time series values of coital patterns and pregnancy are converted to 0s and 1s that is, for any day intercourse occurs, "1" is replaced with "a" and 0 for day with no intercourse, while "1" is replaced with "a" and "0" with "b" for pregnancy feature values. Using python 3.9 and pre-processed generated dataset, extended LSTMUE was implemented, and *Figure 6* describes the AUC-ROC evaluation result of the extended LSTMUE. Compared with the LSTMUE 60% (0.6) AUC-ROC result, as shown in *Figure 6*, the extended LSTMUE produced a better AUC-ROC result of 65% (0.65).

Figure 6: AUC-ROC evaluation of LSTMUE (B) and Improved LSTMUE (A)

A) Improved LSTMUE AUC-ROC



B) LSTMUE AUC-ROC



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DISCUSSION

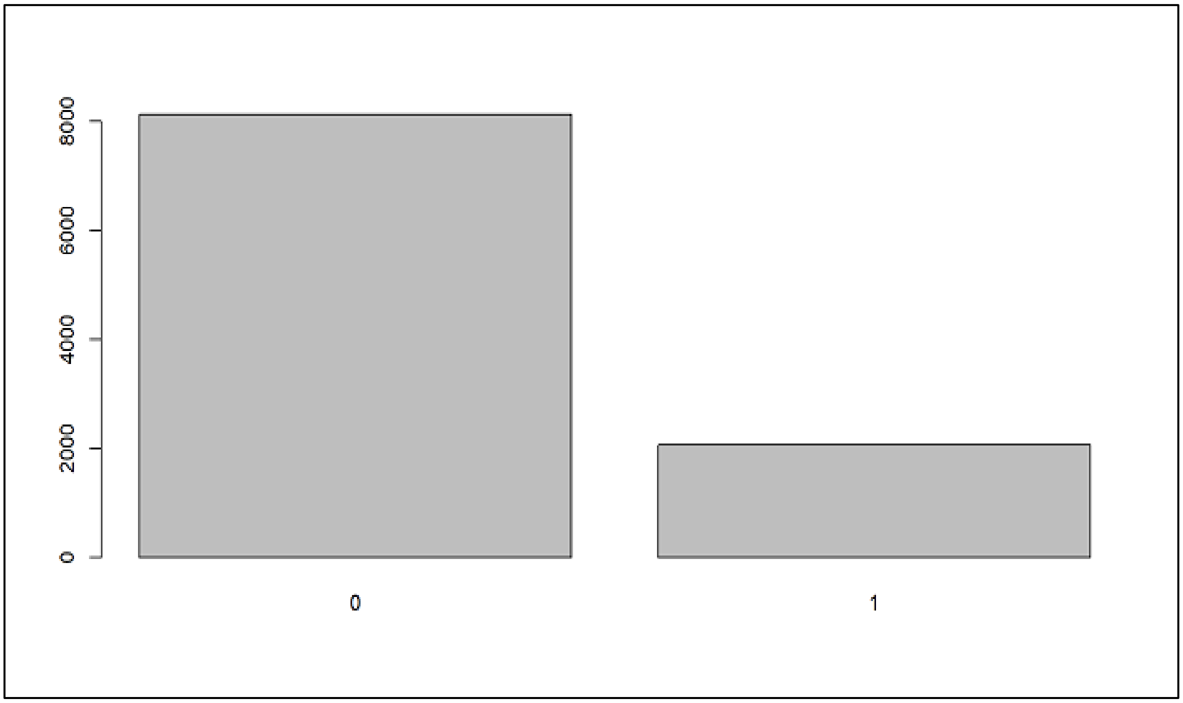
With respect to the data size problem identified in the medical study data collection approach, the data collection approach adopted for this study generated a large size dataset due to the adoption of the internet-based platform (Google form platform), which is more convenient (fill at participants' time and location convenience) to use. For instance, Colombo and Masaratto's (2000) medical study which generated a fecundity dataset of 732 participants within a study space of a one (1) year, cannot be compared with this study's fecundity dataset of 2838 participants which was also collected within the space of one (1) year. The earlier fecundity study's dataset was observed to be one of the most used fecundity datasets for fecundity analysis and modelling. Compared with other fecundity datasets from fecundity studies like Stanford and Smith (2000) and Buck Louis et al. (2011) which generated a reasonably higher fecundity dataset size, this study used a period of one (1) year to collect its dataset, whereas more than a year were used in their studies.

Although Mikkelson *et al*. (2009) adopted a web-based fecundity study and collected a large-size fecundity dataset, this study proposes a cheaper web-based platform (Online Google form) for data collection. Also, this study proposed the parallel usage of a web-based data collection platform and the conventional data collection platform (questionnaire) so as to accommodate participants with less knowledge of web-based platform usage.

The internet-based platform is similar to the HTMA platform, while the other data collection approach (filling of a questionnaire) adopted by this study is similar to the Medical study approach which generated a much smaller size of data. Unlike the high missing data problem attached to the HTMA data collection approach, this study approach reduced the problem to a minimum by enabling data entry supervision (follow-ups) which was adopted in the medical study data collection approach.

The improved LSTMUE model performed better than the existing LSTMUE in predicting intercourse heterogeneities that will lead to pregnancy, but the evaluation result is nevertheless low. The proposed fecundity dataset was observed (as in *Figure 7*) to be highly imbalanced with the number of cycles with negative pregnancy outcomes higher (almost 5 times) than the number of cycles with positive pregnancy outcomes. The imbalanced nature of the dataset affected the evaluation result of the LSTMUE models. The use of the AUC-ROC estimates for evaluation of the proposed models gave a better picture of the model's performance due to its specific evaluation method (that is, focusing on evaluating the performance on classifying one of the classes (positive cycles) and then using the results to evaluate the performance on classifying the other class (negative cycles)). The imbalanced nature of the dataset had less effect on the AUC-ROC estimation.

Figure 7: Proposed Fecundity dataset strata based on cycles with positive (1) and negative (0) pregnancy outcome



Furthermore, it was observed that the problem of class imbalance identified with this study's proposed fecundity dataset also affects previous research like Colombo and Masaratto (2000), Liu *et al.* (2019) and more. However, it is known that due to infertility or subfertility, couples trying to get pregnant using similar efforts as fertile couples could still end up not achieving pregnancy at all (for infertile couples) or after more than one cycle (sub-fertile couples). This implies that there are cycles with negative pregnancy outcomes that may contain daily intercourse occurrence behaviour similar to the cycles with positive pregnancy outcomes. Out of 2838 participants, 2064 recorded pregnancy; this implies that a reasonable size number of the 2064 pregnant participants got pregnant as subfertile participants; thus, a reasonable number of cycles with similar details as cycles with positive pregnancy outcomes will end up with negative pregnancy outcomes. The implication of this problem is that there is a high number of cycles outliers in the No pregnancy cycles. Future research could be carried out to improve the performance of the improved LSTMUE by reducing the imbalance nature of the dataset through possible outlier cycles removal from the No pregnancy cycles.

CONCLUSION

Fecundity prediction models have been proposed to help support the fecundity prediction process. To develop fecundity prediction models, statistical and computational methods are used based on fecundity factors definitions. LSTMUE is a fecundity prediction model developed using the LSTM model to capture subfertility heterogeneity during fecundity prediction. However, the subfertility definition used was weak and affected the performance of the LSTMUE model. To improve the performance of LSTMUE, this study improved the definition of subfertility used. Fecundity prediction models are implemented after development so as to evaluate the performance of the model using fecundity datasets. To achieve a better fecundity dataset for implementation and evaluation of the proposed extended LSTMUE, this study proposed a hybrid data collection approach.

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