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Machine Learning Prediction Models for Postpartum Depression, a Review of Literature

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Abstract: Postpartum depression is a medical condition which continue to affect many mothers after delivery even though the disease can be prevented. It consequently exposes mothers and family members to illness and even death. Families, governments and other stakeholders incur heavy expenditure in the management of the disease. Research studies have been done to develop machine learning models for prediction of mothers at risk of postpartum depression during pregnancy for preventive measures. This paper presents a literature review of the machine learning prediction models which have been developed for the condition with specific focus on feature selection methods, algorithms used and the resulting performance. Literature review was done with google scholar integrated to an online institutional account for e-resources from e-databases accessed by subscription or free access. Inclusion involved all articles with the key words "machine learning, prediction model, postpartum depression" in the articles dated from 2018 to 2022 and sorted by relevance. A total of 3430 articles were listed while only 17 which were accessible with full text were eligible and therefore selected for the study. Analyzes were done using Microsoft Excel and descriptive analysis. Findings and conclusions will inform scientists on the status of research in the area to guide new studies, and inform the market on the potential benefits of integrating machine learning models in their systems.

Keywords: Machine learning, prediction, model, postpartum depression

1. INTRODUCTION

1.1 Machine Learning

Advancement in computing technology has given rise to alternative methods of operation across various industries leading to improvement on service delivery. A notable example is machine learning (ML) technology which creates artificial intelligence in computer systems to aid them in solving new problems. ML is a technology which makes computers to study and simulate human activities so as to acquire artificial intelligence that enables them to learn from experience using historical data and apply the knowledge acquired to solve similar problems without explicit reprogramming[1]. Information is extracted from complex datasets which enable computers to make intelligent decisions which improves their performance. It is an emerging technology triggered by improved methods of capture and storage of data following the advancement of data management techniques. ML technique is derived from the methods traditionally used to analyze data inputs and extract information which include mathematics, statistics, data mining, optimization and artificial intelligence[2].

According to Lai *et al*, three different methods of ML can be used which includes supervised learning which uses labelled datasets to develop a model, the unsupervised learning which can discover data patterns automatically from unlabeled dataset based on a given criteria, and reinforcement learning which also uses unlabeled dataset whereby learning is achieved through experience from interaction with the environment. A range of different algorithms can be used to train ML models and select the best performing model[3][4]. The ML process entails collection and preparation of training and test datasets for model development. By the use of specialized ML tools, training is done on a training dataset to create a preliminary model where the pattern between the input and output data is established. The resulting model is tested with unlabeled dataset purposely set aside for testing the model to confirm its accuracy in predicting outcome from new data input.

ML models can be used in various domains to predict events or conditions for awareness so as to prevent or plan on how to counter them. It can specifically be used to support medical personnel in the prediction postpartum depression for pregnant mothers using antenatal data to improve management of the condition. This study could help identify gaps in ML prediction models for postpartum depression and serve as background for development of new prediction models.

1.2 Feature selection and ML algorithms

The choice of the feature selection method and machine learning algorithm used in model development is an important stage in machine learning which will determine the reliability of the developed model. Features in ML are the inputs to a model while the output is described as the response or independent variable for a model [5]. A research problem could have a wide range of input characteristics while only a given fraction of the variables is significant in predicting the target variable. Model development should thus be an elaborate process involving careful feature selection which can accurately predict the correct outcome. This is achieved through different feature selection procedures which are compared during model training to select a method which can produce the most optimal features. The feature selection methods which have been used in healthcare prediction

models include random forest[6], sequential feature selection[3], optimizer[7] and SelectKBest[8]. Expert judgement can also be used by experienced personnel to select features but the automated methods have proved to give better performance[4]. different machine learning algorithms are also suitable for specific kinds of problems and should therefore be carefully selected when developing models. Algorithms such as support vector machines, decision tree, regression and Naïve Bayes are suited for supervised classification models while K-means is suited to unsupervised classification[9]. Whereas a range of algorithms could be suited for a certain kind of problem, model development should involve trial of several selected algorithms for comparison in order to select the most the best performing choice. Feature selection methods should also be tried with different ML algorithms in different environments during training to identify the combination those circumstances.

1.3 Postpartum depression

Good health and well-being is one of the 17 Sustainable Development Goals (SDGs) of the United Nations(UN) which the body seeks to achieve by the year 2030[10]. Among these health concerns is postpartum depression (PPD) which affects about 10% to 20% mothers after delivery, and could by extension have serious effects on the new born baby and other family members[4]. The prevalence rates are not collectively accepted as a reflection of the actual rate since different studies have shown varying rates while there is belief that many cases are not reported. PPD is a serious mental health which can affect mothers for up to one year after delivery[3]. Victims of the condition exhibit associated signals such as sleep disorder, irritability, anxiety, and stress. Worse cases could include intents to murder or commit suicide which can be actualized if proper intervention is not given to the victims in good time. Its effect on children can continue beyond childhood with problems such as weight loss, mental retardation, poor physical growth and other vulnerabilities[11]. Medical personnel use self-reporting questionnaire tools and hospitals personnel expertise to predict the risk of PPD as there are no laboratory methods for the prediction[4][12]. W. Zhang *et al* identified a range of antenatal features like demographics, psychology, diagnoses and client environment as essential characteristics for the prediction of PPD during pregnancy. ML can be integrated to data management systems and use such features to develop systems which can reliably predict mothers at risk of PPD during pregnancy for better management of the condition. The aim of this study was to analyze the feature selection methods and ML algorithms used in the development of ML prediction models for PPD and the resulting performance.

2. RELATED STUDIES

A survey of past review studies on the machine learning models was necessary to reveal the trend in feature selection methods, algorithms used and the resulting performance as summarized in table 1. [13] Carried a scoping review using Arksey and O'Malley frameworks from health and information technology databases covering a period of 12 years. Supervised machine learning technique was used by the entire publications covered while the different algorithms used produced varying performing outcomes with the Area Under the receiver operating characteristic Curve (AUC) ranging from 0.78 to 0.93. The studies did not report on the feature selection procedures used but revealed the potential of using ML technique in the prediction of PPD. Repeated modelling of the different algorithms as concluded by the author could help identify the most suitable combination of feature selection procedures and ML algorithms alongside other parameters to create better performing models. Another literature review by[14] using the PubMed and Embase databases found support vector machine to be the most popular algorithm while all the studies achieved a AUC of over 0.7 which was considered as an acceptable performance in the prediction of PPD. Feature selection methods were not reported but further studies were recommended to advise how such models could be applied in actual practice to support healthcare predictions. Another review by [15] found Bayes Net classifier to be the best performing model (AUC=0.93) compared to support vector machine (SVM), decision trees and neural networks, among others. The feature selection procedure used was not reported. The author concluded that the findings of the literature review was an opener to further research which is a recommendation for further research.

These studies revealed that PPD prediction models developed achieved over 70% accuracy which was considered satisfactory for implementation of the technology in health management. Support vector machine was the most frequently used algorithm while Bayes Net classifier and logistic regression produced the most accurate performance (AUC of 0.93). The other algorithms which achieved a 70% accuracy or higher model performance are Random forest, XGBoost and logistic regression which revealed the potential of ML in the prediction of PPD. A limited number of review studies were found which applied machine leaning to predict the condition. The few review studies also missed to report on feature selection procedures used for the past prediction models. These gaps justified the need for another review to provide missing information and report on progress achieved from recent research studies.

Author / year	**Feature selection Methods**	**Most used Algorithms**	**Performance**
[15], 2020	Not reported	Bayes Net classifier	AUC=0.93
[13], 2021	Not reported	logistic regression	AUC= 0.93
[14], 2022	Not reported	SVM	AUC >0.70

Table 1: Summary of feature selection methods and ML algorithms from related studies

3. METHODOLOGY

3.1 Search criteria

A web-based search with google scholar integrated to an institutional online e-resources account was used to retrieve primary research publications accessible through subscription or open access. The key search words used (model AND prediction AND depression postpartum OR postnatal "machine learning") were formulated from the research objectives and Boolean operators to retrieve required articles. The search which was done in the month

of April to early May 2022 also applied filters to select primary articles and limit target period to the years 2018 to 2022 which were sorted by relevance as shown in figure 1.

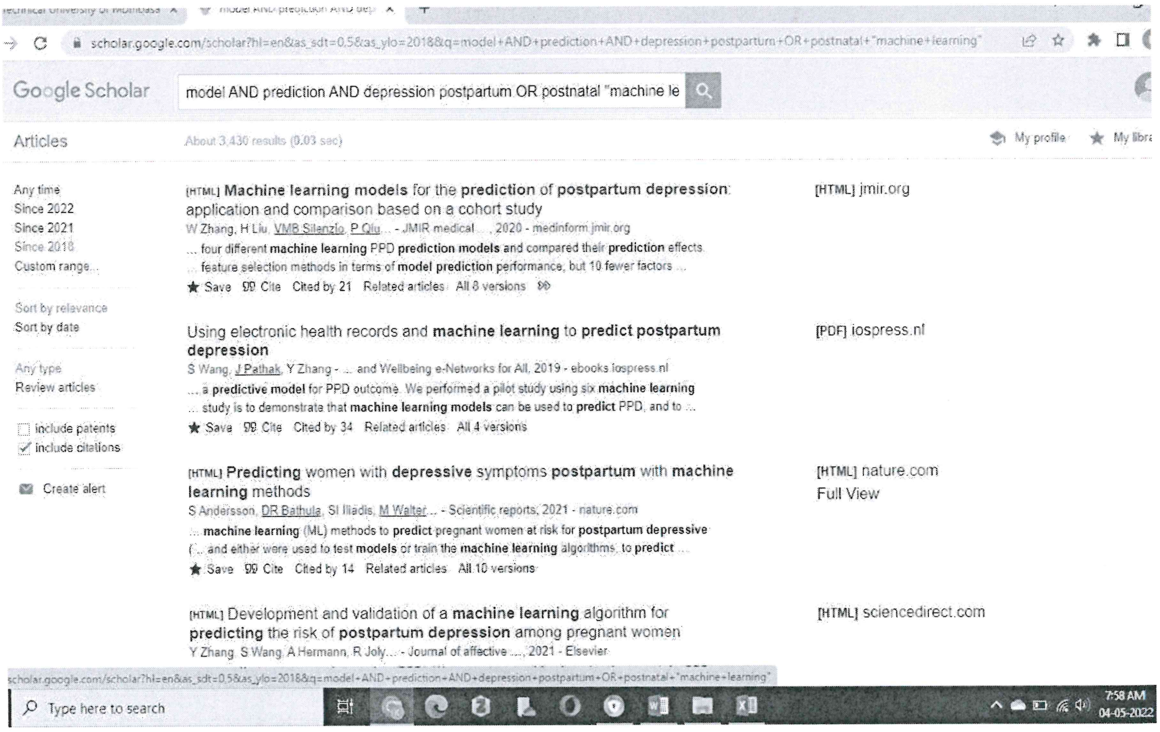

Figure 1: A cross-section of the web search result for eligible publications

3.2 Inclusion and exclusion

Articles for inclusion were primary publications that used antenatal and postnatal data in modelling and specifically for prediction of postpartum depression. The models should have been developed using machine learning technique and the publication period dated from the years 2018 and 2022. The studies for inclusion must have used medical records that originated from hospital sources for the analysis. Articles using secondary publications or those which their full text was not accessible were excluded. Articles on detection of depression which did not focus on future prediction of postpartum depression were also excluded. Retrieval and analysis of the articles was done from Aril to early May 2022. The articles retrieved in the initial search were screened for eligibility by two researchers who evaluated the titles and abstracts. Duplicate and irrelevant articles, and studies which did not use data from hospital medical records sources or which were not specifically focused on future prediction of PPD were excluded.

3.3 Data collection and analysis

Feature selection procedures, ML algorithms and performance of the developed models were extracted by reading the abstracts, methodology, results and conclusion sections of the eligible articles which were captured in table 2. A narrative synthesis of the data was done for the articles in regards to the research criteria. The analysis revealed the findings which supported the conclusions made which could help scientists know the status of research in the area and inform the market about the potential benefits of integrating machine learning models in their systems. This was also important for future studies in the development of new ML models for prediction of PPD to fill gaps identified.

4. RESULTS

4.1 Search process results

A total of 3,430 articles were identified from the initial search process which were subjected to screening out of which 3173 consisting of duplicates, non-articles and irrelevant articles were excluded. The remaining 255 articles were evaluated for eligibility out of which 239 articles were excluded due to missing of the full text and failing to use data from hospital record sources. A total of 16 articles which were found to be eligible were included for the study as illustrated in figure 2.

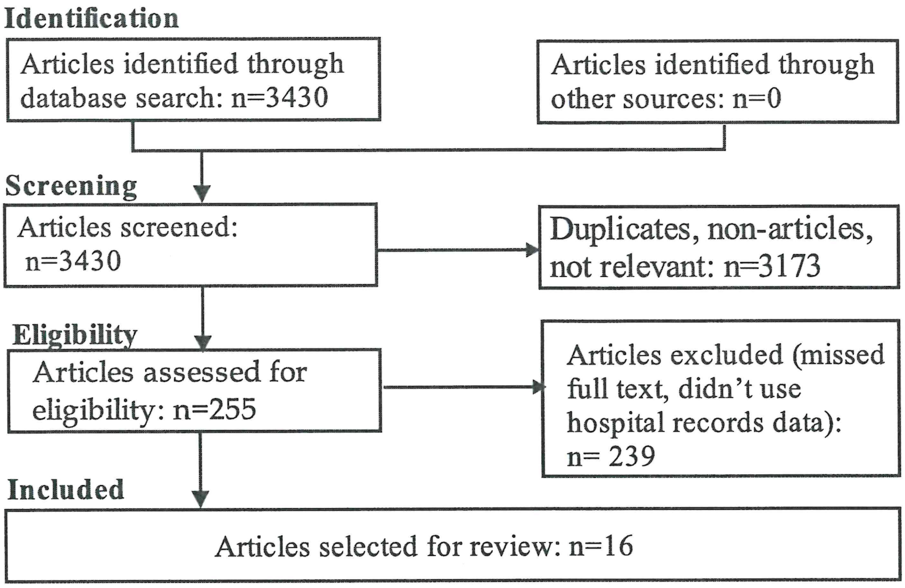

Figure 2: Search process for eligible publications

Table 2: Summary of result for selected studies, feature selection methods and ML algorithms used

SN	Author / Year	Title of publication	Feature selection method	ML Algorithm used	AUC
1	[3], 2021	Development and validation of a machine learning algorithm for predicting the risk of postpartum depression among pregnant women	SFS	Logistic regression with L2 regularization	0.937
2	[16], 2021	Recommender System for Postpartum Depression Monitoring based on Sentiment Analysis	NLP	Text mining	0.88
3	[17], 2021	Predicting women with depressive symptoms postpartum with machine learning methods	Gini Importance or MDI	Extremely randomized trees	0.73
4	[8], 2021	An in-depth analysis of machine learning approaches to predict depression	SelectKBest	AdaBoost	0.96
5	[6], 2021	Predicting Individuals Mental Health Status in Kenya using Machine Learning Methods	RF Classifier	Voting-Ensemble	0.85
6	[17], 2021	A Community Based Study for Early Detection of Postpartum Depression using Improved Data Mining Techniques	J48 algorithm	Adaptive Boosting Collaboration	0.94
7	[18], 2021	Estimation of postpartum depression risk from electronic health records using machine learning	SHAP	Gradient tree boosting algorithm	0.844
8	[19], 2021	Development and validation of a machine learning-based postpartum depression prediction model: A nationwide cohort study	gradient-boosted decision tree	XGBoost	0.712
9	[20], 2021	Machine Learning Models for the Prediction of Postpartum Depression: Application and Comparison Based on a Cohort Study	FFS-RF	SVM	0.78
10	[21], 2020	Depression Detection using Machine Learning	Vectorization	Naïve Bayes	0.936
11	[22], 2020	Data-Driven Insights towards Risk Assessment of Postpartum Depression.	ReliefF expRank	RF	0.75
12	[23], 2020	Machine learning-based predictive modeling of postpartum depression	Relief algorithm	RF	0.885

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13	[4], 2020	Using Machine Learning and Electronic Health Records to Predict Postpartum Depression	FFS-RF	SVM	0.78
14	[24], 2020	The application of machine learning in depression	Optimizer	RF	0.9655
15	[12], 2019	Prediction of postpartum depression using machine learning techniques from social media text	LIWC tool	MLPs	0.9163
16	[25], 2019	Using electronic health records and machine learning to predict postpartum depression	Feature comparison, then univariate LR analyses	SVM	0.79

Key: - SFS - Sequential feature selection, NLP- natural language processing, MDI- Mean Decrease in Impurity, LR- logistic regression, SHAP-Shapley additive explanations Processing, FFS-RF -random forest-based filter feature selection, MLPs- Multilayer perceptrons

5. ANALYSIS AND DISCUSSION

Analysis of reviewed publications found that a total of 14 feature selection methods and 11 ML algorithms were used in all the 16 publications studied as shown in tables 3 and 4 respectively. The highest percentage (18.75%) of publications used random forest-based feature selection method while each of the other methods had a single frequency in the remaining articles with a percentage of 6.25% as shown in figure 3. On the other hand, SVM was the most used ML algorithm by 18.75% of the articles, followed by RF and Adaptive Boosting Collaboration algorithms at 12.5% each as shown in figure 4. Each of the other algorithms namely extremely randomized trees, Logistic regression with L2 regularization, Text mining, XGBoost, Voting-Ensemble, Gradient tree boosting algorithm, MLPs and Naïve Bayes had a single frequency in the remaining publications with a percentage of 6.25% of the articles. The performance of all the models developed had an AUC of over 0.70 while the best performance achieved had AUC of 0.9655 which was from a combination of optimizer feature selection method and RF ML algorithm which signified the potential of ML techniques in predicting PPD and other medical conditions.

Table 3: Feature selection methods used and their frequency

Sn	Feature selection Method	Number of publications
1	Sequential feature selection	1
2	Natural language processing	1
3	Gini Importance or Mean Decrease in Impurity	1
4	SelectKBest	1
5	Random forest	3
6	J48	1
7	Shapley additive explanations Processing	1
8	Gradient boosted decision tree	1
9	Vectorization	1
10	ReliefF expRank	1
11	Relief	1
12	Optimizer	1
13	LIWC tool	1
14	Feature comparison, then univariate logistic regression (LR) analyses	1
	TOTAL	16

Table 4: ML algorithms used and their frequency

Sn	ML algorithm	Number of publications
1	Logistic regression with L2 regularization	1
2	Text mining	1
3	Extremely randomized trees	1
4	XGBoost	1
5	Voting-Ensemble	1
6	Adaptive Boosting Collaboration	2
7	Gradient tree boosting algorithm	1
8	Naïve Bayes	1
9	Support vector machine	3
10	Random forest	2
11	Multilayer perceptrons (MLPs)	1
	TOTAL	**16**

The high variation in feature selection methods and ML algorithms used could be a revelation that scientists were yet to settle on the best parameters for an optimal prediction model which qualified the need for continued research on the subject matter. The variation could also have arisen from the need to address specific research objectives which were the focus of the different authors. The Naïve Bayes classifier which tied with logistic regression as the best performing algorithm from the related studies maintained its performance (AUC of 0.93) even though it did not perform a well as other models like AdaBoost (AUC of 0.96), RF (0.9655) and Adaptive Boosting Collaboration (AUC of 0.94). The consistency could not be explained since the feature selection method used from related studies was not reported.

RF, SVM and Adaptive Boosting Collaboration algorithms drew more interest among the researchers and produced a mixed performance when combined with different feature selection methods. RF algorithm which produced the best model (AUC of 0.9655) when used with optimizer feature selection method also produced the second lowest performance (AUC of 0.75) when combined with ReliefF expRank feature selection method. SVM ML algorithm which had the highest frequency of use by the different authors produced a low performance in all the instances (AUC <0.80) when used with FFS-RF and feature comparison followed by univariate LR analyses feature selection methods. The mixed performance by the algorithm could be an indicator that the high performing combination needed finetuning with repeated trials in different environment to confirm their reliability while as other studies are undertaken to explain the cause of the low performing combinations. The combination of SVM ML algorithm and FFS-RF feature selection methods produced a lower performance outcome (AUC of 0.78) which was the same in two different studies. More studies are needed understand the cause of the performance which should also be done in different environments to confirm the consistency. The lowest performance was from a combination of XGBoost ML algorithm and gradient-boosted decision tree feature selection method (AUC of 0.712). Trials of the same combination of feature selection method and ML algorithm should be undertaken in different environment to evaluate the performance and determine their reliability.

Even though random forest-based feature selection method had the highest frequency of publications, the studies which used the method did not produce the best performing model. Equally, the models created from SVM which was the most frequently used ML algorithm did not produce the most accurate result[4]. The best model was developed from a combination of optimizer feature selection method and RF ML algorithm (AUC of 0.9655) which was almost similar to the next performing model produced from a combination of SelectKBest feature selection method and AdaBoost ML algorithm (AUC=0.96). RF algorithm which produced the best model with Optimizer feature selection method was also used by most studies proving it to be a reliable choice for future models. Whereas these trials provided informative outcomes based on the choices made and their combinations and the environment in which they were used, it was apparent that more research was necessary to finetune the models before adoption. The RF-based feature selection method which was the most popular procedure did not produce the best model when used with RF ML algorithm; its combination with SVM produced a better model[4]. Optimizer feature selection had the least trials but produced the best model. Its high performance needs to be qualified through trials in different environments in combination with other algorithms for comparison. The percentage of publications used for feature selection methods and ML algorithms is shown in figures 3 and 4.

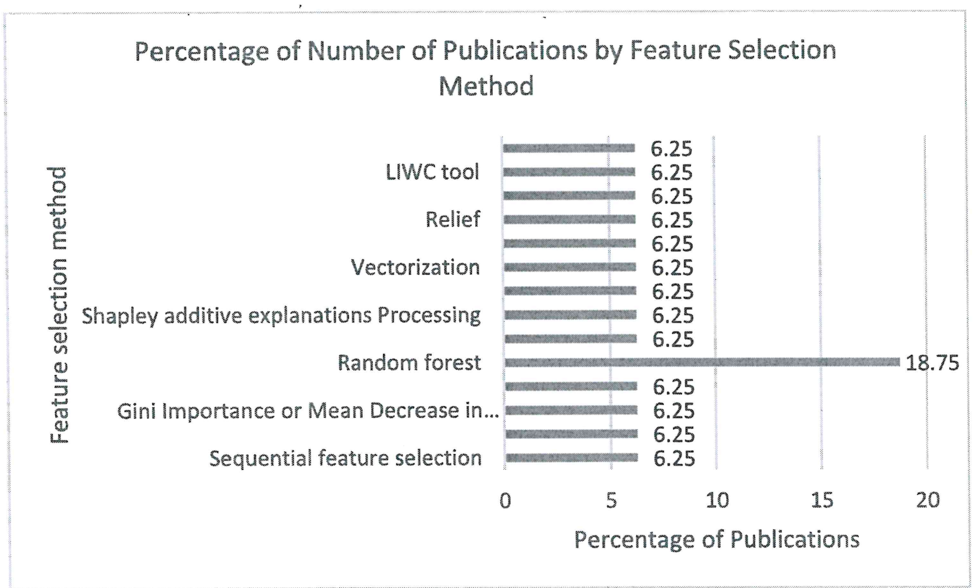

Figure 3: Analysis of feature selection methods by the percentage of publications

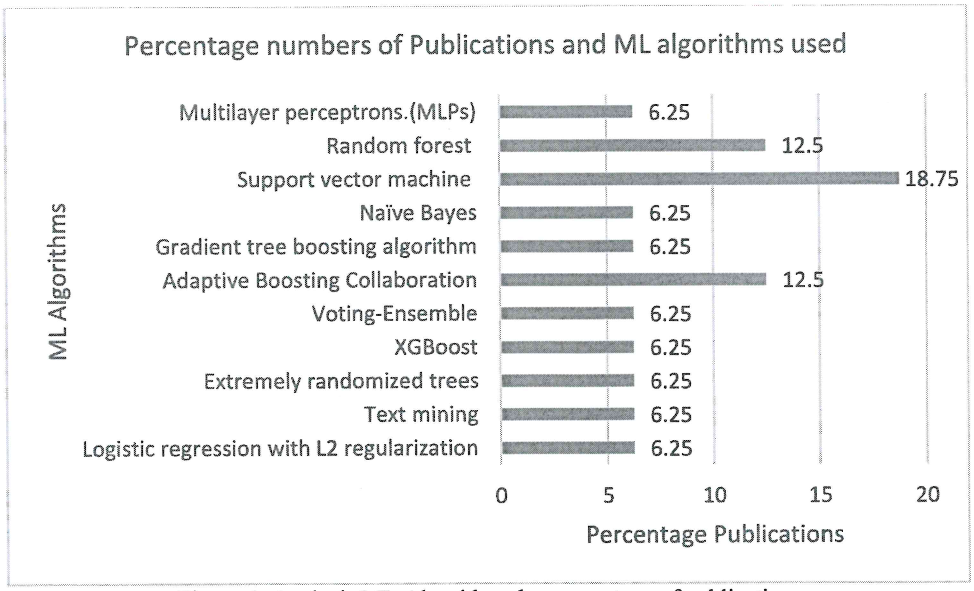

Figure 4: Analysis ML Algorithms by percentage of publications

6. CONCLUSION

The models developed from the review studies produced high performance measures which reflected that ML had great potential to be applied in the prediction of PPD and other medical conditions. Despite the high performance noticed, there was no consistency in the choice and performance of the algorithms used for feature selection and modeling. More trials are required considering the fact that the approaches which were not the most popular choices produced better performance which may not have been expected. The feature selection methods and ML algorithms should be tested under different environments while at the same time interchanging their combinations to compare their performance. It can be concluded that ML algorithms and feature selection methods have not been given enough trials to support a credible analysis of their performance and eventual ranking. More collaborative studies which should consider other contributing parameters in modelling should be carried out for comparison.

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