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PAPER

Prediction of Depression via Supervised Learning Models: Performance Comparison and Analysis

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ABSTRACT

This document Among all the various types of mental and psychosocial illnesses, the most commonly occurring type is depression. It can cause serious problems such as suicide. Therefore, early detection is important to stop the progression of this disease that could endanger human lives. Predicting and detecting early-stage depression using machine learning (ML) techniques is a promising strategy. This study's main purpose is to assess which ML techniques are highly appropriate and accurate regarding such diagnoses. Six supervised ML techniques namely: K-nearest neighbor (KNN), Random Forest (RF), Logistic Regression (LR), Decision Tree (DT), Support vector machine (SVM) and Naive Bayes (NB) were applied on dataset collected from Kaggle and compared for their accuracy (ACC) and performance in predicting depression. The performance of each model was evaluated using 10-fold cross-validation and evaluated in terms of ACC, F1-score, Precision (PR), and Sensitivity (SEN). Based on the experimental results analysis, we can conclude that SVM and LR performed better than all other methods with an ACC of 83,32%. Therefore, we found that a simple ML algorithm can be used to assist clinicians and practitioners predict depression at an early stage, with excellent potential utility and a considerable degree of ACC.

KEYWORDS

Machine learning, K-NN, DT, SVM, NB, LR, Algorithms, Depression

1 INTRODUCTION

The world is advancing rapidly due to human and technological skills. To cope with the world's rapid pace of change, people constantly place stress on their bodies and minds that negatively affects their health, especially their mental state. A popular mental disorder is depression and all individuals, at a particular time in their lives, are depressed. Depression is a mental disorder that can be recognized by different symptoms leading to functional impairments in activities of daily living [1].

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According to the World Health Organization (WHO), depression is the most prevalent mental illness, affecting more than 300 million people worldwide [2]. Because of the severity of that problem, many health researchers have chosen to concentrate their research on this field. It represents a significant challenge to healthcare systems. That is why it is considered as the leading factor in non-fatal health loss. It leads to an inability to accomplish daily functions, and people with depression lose their interest and enjoyment in the activities they usually like to do [3]. As a result of depression many chronic diseases, like diabetes [4], [5] and heart disease [6], etc., can be developed in depressed people. The reason why it is the second most important factor in the development of chronic diseases [7], [8]. Suicide cases may be prompted on by severe depression, which may have, in long-term, a detrimental effect on the country's socioeconomic situation as well [7]. Before counselling a person for depression, the most crucial task is to identify if the person is depressed or not. Therefore, a predictive model is needed to determine if individuals are at risk for becoming depressed. ML has generated significant interest from researchers in the development of intelligent digital health procedures [9]. These procedures have the power to potentially transform healthcare and provide robust outcomes for the healthcare professionals and patients [10]. However, the use of ML techniques to recognize and forecast depression has received very little attention. The prediction of depression in the future is significant as it enables preventive procedures to be implemented to ease the burden of depression. In order to close this gap, this research offers a cutting-edge alternative. The objectives of this research are 1) to predict depression disease outcome using ML techniques 2) to compare ML techniques to obtain better performance and identify the classifiers that are able to predict depression disease efficiently enough to be clinically useful. We have used six algorithms namely KNN, RF, NB, LR, DT and SVM to execute our model to determine and predict depression disease, using online depression dataset from kaggle.

The remaining sections are arranged as follows: After providing an overview regarding depression occurrence, selected background literature in this area was reviewed in Section 2. Subsequently, a deep explanation of the algorithm implementation process is described in Section 3. Thus, the comparison of the outcomes based on four metrics has been discussed in Section 4. Finally, the Paper was concluded in Section 5, presenting some possible areas for further work.

2 LITERATURE REVIEW

Several researches have successfully investigated prediction techniques for depression diagnosis. An overview of studies is provided below based on these three selection criteria: (1) the study concerns depression; (2) it employs ML algorithms; and (3) it evaluates and measures depression using predictive models.

Anu Priya et al. [11] performed prediction of depression using five ML algorithms – namely DT, RF, NB, SVM and KNN. The data was collected through the DASS-21 questionnaire from 348 participants aged 20–60 years, to rank the Depression, Anxiety and Stress Scale. According to the results, the best ACC depression scales was obtained by NB [11].

Arkaprabha Sau and Ishita Bhakta [12] studied the prediction of anxiety and depression in the older patients using the ML methods. Data collection was done from 520 geriatric patients in the period of January to August 2016. All patients were assessed for anxiety and depression using the Hospital Anxiety and Depression Scale (HADS) by the investigator. A total of ten classifiers including Bayesian network (BN), logistic, multi-layer perceptron (MLP), NB, RF, random tree (RT), J48, sequential minimum optimisation (SMO), random subspace (RS) and K-star (KS) were applied and evaluated. The highest ACC was achieved by RF. The same RF model was also evaluated on another dataset of 110 separate elderly patients for external validity. It had an ACC of 91% prediction and a false positive (FP) rate of 10%, compared to the reference tool. The results clearly show that RF is the suitable algorithm for the dataset used in the study [12].

Ishita Bhakta and Arkaprabha Sau [13] applied ML classifiers to predict depression in the elderly. Sixty elderly people were questioned with the use of the Geriatric Depression Scale (GDS) to gather data. Five different learning methods were applied – BN, Logistic, Multi Layer Perceptron, SMO and Decision Table – and compared on four parameters – ACC, ROC area, PR and Root Mean Square Error (RMSE). BN performed better in the percentage split tests for these four parameters [13].

For developing a predictive model for Postpartum Depression (PPD), a research study was proposed by Shuojia Wang et al. [14]. This was achieved by using six ML techniques, such as LR regularised by L2, SVM, DT, NB, Extreme Gradient Boosting (XGBoost) and RF [14]. Results from the 6 ML models using 98 predictors have shown that the AUC of SVM was the highest, and the lowest was for DT. Then, the SEN and specificity (SPE) of all algorithms were calculated. The NB had the highest SPE (61.6%) and the lowest SEN (86.7%) in contrast to DT model.

Similarly, Weina Zhang et al. [15] investigated the predictors of postpartum depression among 508 women in China [15]. For this study, two different ML feature selection methods and two ML algorithms (SVM and RF) were combined to compare the impact of PPD prediction models, decide on the ideal predictive model. As a result, four different ML prediction models of PPD were constructed and then compared. The SVM and FFS-RF based model showed the highest prediction effects (SEN=0.69, area under the curve=0.78).

Using ML algorithms, Sabab Zulfiker et al. [16] intended to determine the most appropriate ML method for detecting depression using Burns Depression Checklist to evaluate each participant's actual level of depression. The data set is made of 604 responses [16]. Their work considered six ML techniques: KNN, Adaptive Boosting (AdaBoost), Gradient Boosting (GB), Bagging, Weighted Voting, and XGBoost. The features were selected using three methods, including the Boruta feature selection algorithm, K-Best Features (SelectKBest), and Select Minimum Redundancy and Maximum Relevance (mRMR) methods were used to extract the important characteristics from data. Moreover, five assessment parameters, namely SEN, SPE, ACC, F1-score and AUC were calculated for each model with the objective of selecting the most appropriate model for detecting depression. Their results showed that AdaBoost algorithm with the SelectKBest method is the best algorithm with high ACC (92.56%) and AUC (0.96).

Na et al. [9] built a ML-based predictive model for future onset of depressive illness within the Republic of Korea. The study was performed on 6,588 individuals [9] in which SMOTE was utilized to address the problems of class imbalances and the RF classifier was employed to build the predictive model. Overall, the SEN, SPE, and ACC were 0.730, 0.866, and 0.862, respectively. The study also revealed that the main elements influencing the appearance of depression are satisfaction with socio-family relationships and for health.

Christopher M.Hatton et al. [16] investigated the utility of a ML approach to predict the persistence of depressive symptoms in older adults. Baseline demographic and psychometric data from 284 patients were used. They observed that the predictive performance of the XGBoost algorithm ML approach (mean AUC 0.72) was modestly superior to that of LR (mean AUC 0.67). Notably, the XGBoost performance was superior to that of the LR [16].

Arkaprabha Sau, and Ishita Bhakta [17] benchmarked the performance of ML techniques in detecting both depression and anxiety in seafarers. For this purpose, five ML classifiers (CatBoost, LR, NB, RF, and SVM) were evaluated using the Python programming language. The results showed that CatBoost outperformed over all other algorithms, with PR and ACC of 84.1% and 82.6%, respectively [17].

Choudhury et al. [1] have used three techniques to forecast depression in its early stages among the undergraduate students of Bangladesh. The algorithms are KNN, RF and SVM. The survey of this research was administred from July to September 2018 and comprised 935 students. SVM and RF were found to have similar ACC and f-measures of about 75% and 60%, respectively, with RF having a greater PR, recall, and reduced false negatives. RF was shown to be the best algorithm [1]. Table 1 summarises these studies and the models they employed.

Table 1. Research studies based on ML models

Author	Patient Sample	ML Algorithms	Metrics for the Best Algorithm
Anu Priya et al. 2020	348	DT, RF, NB, SVM, KNN	ACC = 0.855 PR = 0.822 Recall = 0.850 SPE = 0.917 F1-score = 0.836
Arkaprabha Sau, Ishita Bhakta 2017	520	BN, logistic, MLP, NB, RF, RT, J48, SMO, RS, KS	ACC = 89% TP rate = 89% PR/PPV = 89.1% F-measure = 89% AUC = 94.3%
Ishita Bhakta, Dr Arkaprabha Sau 2016	60	BN, Logistic, MLP, SMO, Extrem Table	ACC = 0.95 PR = 0.95 ROC = 0.99 RMSE = 0.22
Shuojia Wanga,b, Jyotishman Pathaka, Yiye Zhanga 2019	9980	L2-regularized, LR, SVM, DT, NB, XGBoost, RF	AUC (SVM) = 0.79 SEN (DT) = 98.6% SPE (NB) = 61.6%
Weina Zhang et al. 2020	508	FFS-RF, SVM, RF	SEN = 0.69 SPE = 0.83 PPV = 0.68 NPV = 0.84 Geometric mean = 0.76 ROC-AUC = 0.78

(Continued)

Table 1. Research studies based on ML models *(Continued)*

Author	Patient Sample	ML Algorithms	Metrics for the Best Algorithm
Md. SababZulfiker et al. 2021	604	KNN, AdaBoost, GB, XGBoost, Bagging, Weighted Voting, SelectKBest, Mrmr, Boruta	ACC = 92.56% SEN = 91.89% SPE = 93.62% PR = 95.77% F1-Score = 93.79% AUC = 0.96
Na et al. 2020	6588	RF	ACC = 0.862 SEN = 0.730 SPE = 0.866
Christopher M.Hatton et al. 2019	361	XGBoost LR	ACC = 74% SEN = 0.78 SPE = 0.56 Positive predictive Value = 0.89 Negative predictive Value = 0.35 AUC = 0.72
Arkaprabha Sau, Ishita BhaktaTo 2019	470	CatBoost, LR, NB, RF, SVM	ACC = 82.6% PR = 84.1% Roc = 0.882s
Choudhury et al. 2019	935	KNN, RF, SVM	ACC = 75% PR = 70% Recall = 53% F-measure = 60%

From the above discussion, it can be said that ML is a cutting-edge approach in the domain of predictive models in medical sciences. Several researchers have implemented different ML techniques for the forecasting of psychology problems, and no fixed technique was found to be the most appropriate in all cases. Thus, in the present study, six ML algorithms were applied to predict depression.

3 METHODOLOGY

3.1 Data collection

To implement our predicted model in this study, an open access depression dataset has been handled. Specifically, the dataset was retrieved through Kaggle [18] with a focus on individuals living in rural areas. This dataset contains 1409 patient records with 20 attributes, including 115 males and 1294 females with different age distribution. 16.7% of the patients are depressed and 83.3% are normal, as shown in Figure 1, while Table 2 describes full attributes information.

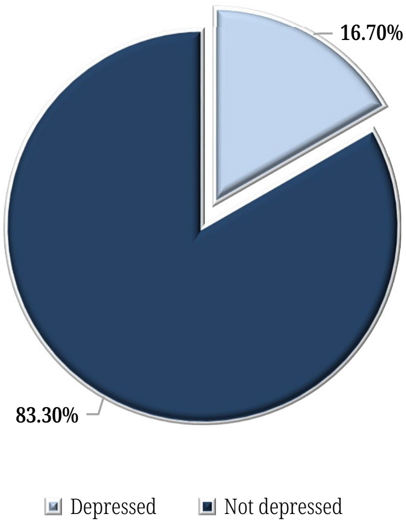

Fig. 1. Distribution of participants with and without depression

Table 2. Attributes description

No	Attribute Name	Attribute Type
1	Age	predictor
2	Married	predictor
3	Number of Children	predictor
4	Education	predictor
5	Total Members	predictor
6	Gained Asset	predictor
7	Durable Asset	predictor
8	Save Asset	predictor
9	Living Expenses	predictor
10	Other Expenses	predictor
11	Incoming Salary	predictor
12	Incoming Own Farm	predictor
13	Incoming Business	predictor
14	Incoming No Business	predictor
15	Incoming Agricultural	predictor
16	Farm Expenses	predictor
17	Labor Primary	predictor
18	Lasting Investment	predictor
19	No Lasting Investment	predictor
20	Depressed	Target

The overall process for the implementation and evaluation of six supervised ML techniques is overviewed in Figure 2 and detailed afterwards.

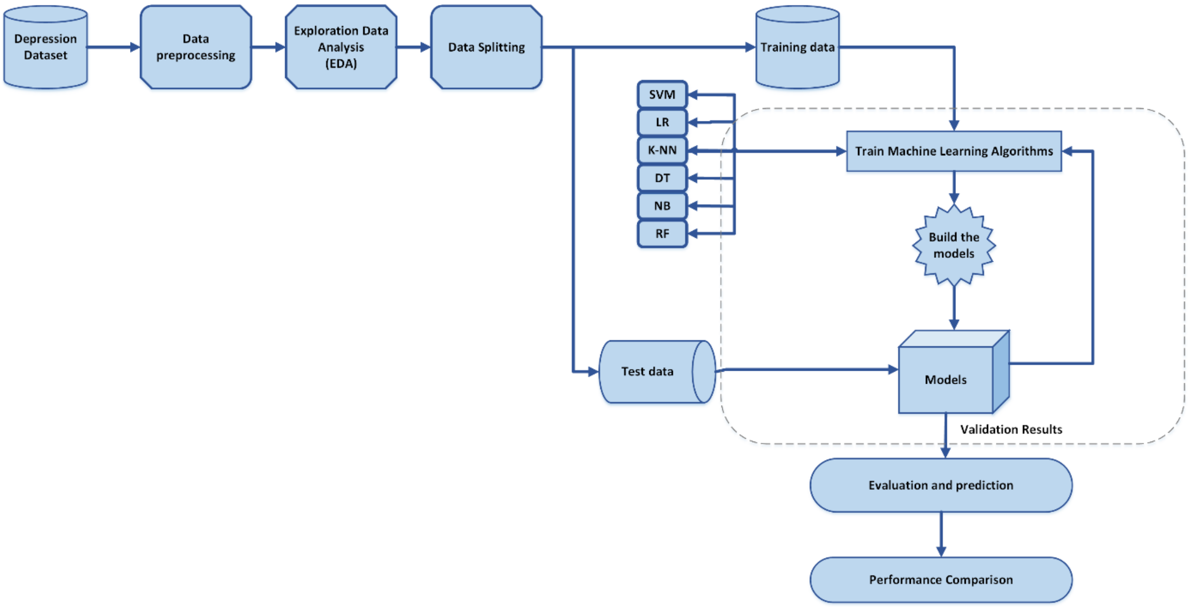

Fig. 2. The workflow of the proposed methodology for depression prediction

3.2 Data preprocessing

The preprocessing of data is required for all ML applications, as the performance of a particular ML algorithm is contingent on the manner in which the dataset has been prepared and structured. Data preprocessing ensures that the data is tailored to the specific requirements of the respective algorithm [19]. Preprocessing techniques includes:

- Remove missing or null values, clean up noisy data, detect and eliminate outliers, as well as fix data inconsistencies.
- Performe Feature selection, out of 22 features, 20 features were selected.
- Normalize and aggregate Data.
- Apply the synthetic minority oversampling (SMOTE) technique to achieve a synthesised class-balanced dataset and improve the predictive ACC of the minority class [20].

Python version 3.3 with different libraries like Panda, Pyplot and Scikit-learn [21] have been utilized to conduct the study, for both exploratory data analysis (EDA) and data visualization. Within training datasets, depressed and non-depressed attendants are 215 and 1053, respectively. Since training datasets are significantly unbalanced, SMOTE has been employed in order to overcome the problem of class imbalance as shown in Table 3.

Table 3. The result of the SMOTE technique

	Depression	
	Yes	No
Before SMOTE	215	1053
After SMOTE	1053	1053

In addition, exploratory data analysis (EDA) was conducted (as a heat map) for detecting correlations between features, and the data were plotted kde for depressed and non-depressed patients by age distribution, also graphically to present the distribution of depression by gender and marital status.

3.3 Justification of the proposed techniques

In this work, six supervised ML algorithms have been selected for depression prediction: LR, DT, RF, SVM, NB and KNN. The criteria behind selecting these algorithms namely is that:

(a) All of the algorithms were extensively employed in health disorder diagnosis and treatment and were proven to exhibit high prediction performance [22].
(b) All used algorithms are able to address classification tasks involving several influencing parameters as well as modeling non-linear relationships [22].
(c) All techniques are among the most influential ML algorithms in the research community and among the top 10 ML algorithms [23].

3.4 ML algorithms

SVM. SVM is a supervised ML model that works with classification and regression analysis. It works by finding the best possible boundary (hyperplane) between two or more classes of data points, based on their features. The SVM algorithm maximizes the margin (distance) between the data points and the decision boundary [22].

KNN. KNN is a supervised ML algorithm that finds the k nearest data points to a given input data point in the training set and then uses the labels or values associated with these k-neighbors to predict the new one. The similarity between the instances can be estimated using distance measures [20].

RF. RF is a classification data technique by combining multiple DTs. It works by randomly selecting subsets of the training data and features to build multiple decision trees. Each tree in the forest is trained on a different subset of the data and features, making them different from one another [22].

LR. LR is a statistical algorithm used for binary classification, which means predicting whether a given input belongs to one of two possible categories. It works by estimating the probability of the input belonging to each category and then classifying it based on which category has a higher probability. The algorithm uses a logistic function to map the input values to the predicted probabilities, and it is trained on a labeled dataset to learn the relationship between the input features and the binary output variable [24].

DT. DT is a ML algorithm that relies on a tree model to make decisions on the basis of input data points. The decision tree recursively divides the data into small sets of variables depending on the characteristic that provides the best gain in information. The evaluation of input variables is represented by all internal nodes that contain at least one child node [11].

NB. NB is a probabilistic ML algorithm used for classification tasks. It works by calculating the probability of a given data point belonging to each possible class and selecting the class with the highest probability as the predicted class. The "naive" part of the algorithm refers to the assumption that all features are independent of each other, which simplifies the calculation of probabilities [11].

3.5 Performance evaluation metrics

The effectiveness of the ML method can be evaluated using performance indicators which help to ensure that the proposed models are being evaluated in a consistent and objective way [25]. In this work, six classification algorithms have been implemented on the dataset for the purpose of finding the most performing algorithm through comparing the ACC, PR, recall or SEN, F1-score. The following subsection describes briefly the performance measures:

A confusion matrix, otherwise referred as the error matrix, is a dedicated table for calculating the performance of a model [22]. All model parameters we used were calculated as follows:

$$ACC = \frac{(\mathrm{TP} + \mathrm{TN})}{(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN})}$$

$$PR = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

$$SEN = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

$$\text{F1-score} = \frac{2*(\mathrm{PR}*\mathrm{SEN})}{\mathrm{PR} + \mathrm{SEN}}$$

Where,

- TP = stands for true positives and represents the number of depressed patients predicted by the algorithms as depressed [20].
- TN = stands for true negatives and represents the number of non-depressed patients as non-depressed ones [20].
- FP = stands for false positives and represents the number of non-depressed patients incorrectly predicted by the algorithms as depressed patients [20].
- FN = stands for false negatives and represents the number of depressed patients incorrectly predicted by the algorithms as non-depressed patients [20].
- ACC is the proportion of instances that a classifier correctly classified [19].
- SEN concerns the proportion of TP that the classifier precisely defines as data and detects the number of correct predictions [19].
- PR measures the percentage of expected positives that are TP [19].
- The F1-score retains a balanced ratio of PR to recall for a classifier [19].

3.6 K-fold cross-validation

The original training set in the k-fold cross-validation (k-fold CV) is then partitioned into k clusters, whereby k-1 clusters have been utilized for training the classifiers while the remaining part has been employed to verify the outperformance within each step [22]. The above procedure is then replicated k times for different folds being used as validation folds and the k-fold CV performance is the average performance realized within each fold. In the present study as recommended by Kohavi [26], the 10-fold CV was implemented based on its strong performance [26]. For each fold, the 10-fold process was iterated and all training and test groups' instances were randomly distributed across the entire dataset before the selection of the new training and test sets for the new cycle. Finally, the averages of all performance metrics were computed after the completion of the 10-fold process.

4 RESULTS & DISCUSSION

4.1 Results of EDA

For a better understanding of the dataset features, exploratory data analyses have been conducted. And a heat map depicting correlated values and correlations among the 20 attributes included in the depression dataset, as can be seen in Figure 3. The variable age is significantly Correlated with the depression attribute with a value of 0.1, although other attributes such as number of children, total number of members, and durable goods exhibited a weak correlation with the output. As a whole, age is strongly related to outcome and is considered as a relevant driver of depression.

Density distribution of participants with and without depression is depicted in Figure 4. It is evident that persons aged 20 to 38 years are the most affected population in the applied dataset. Thus, the graph indicates that age is a significant parameter for depression.

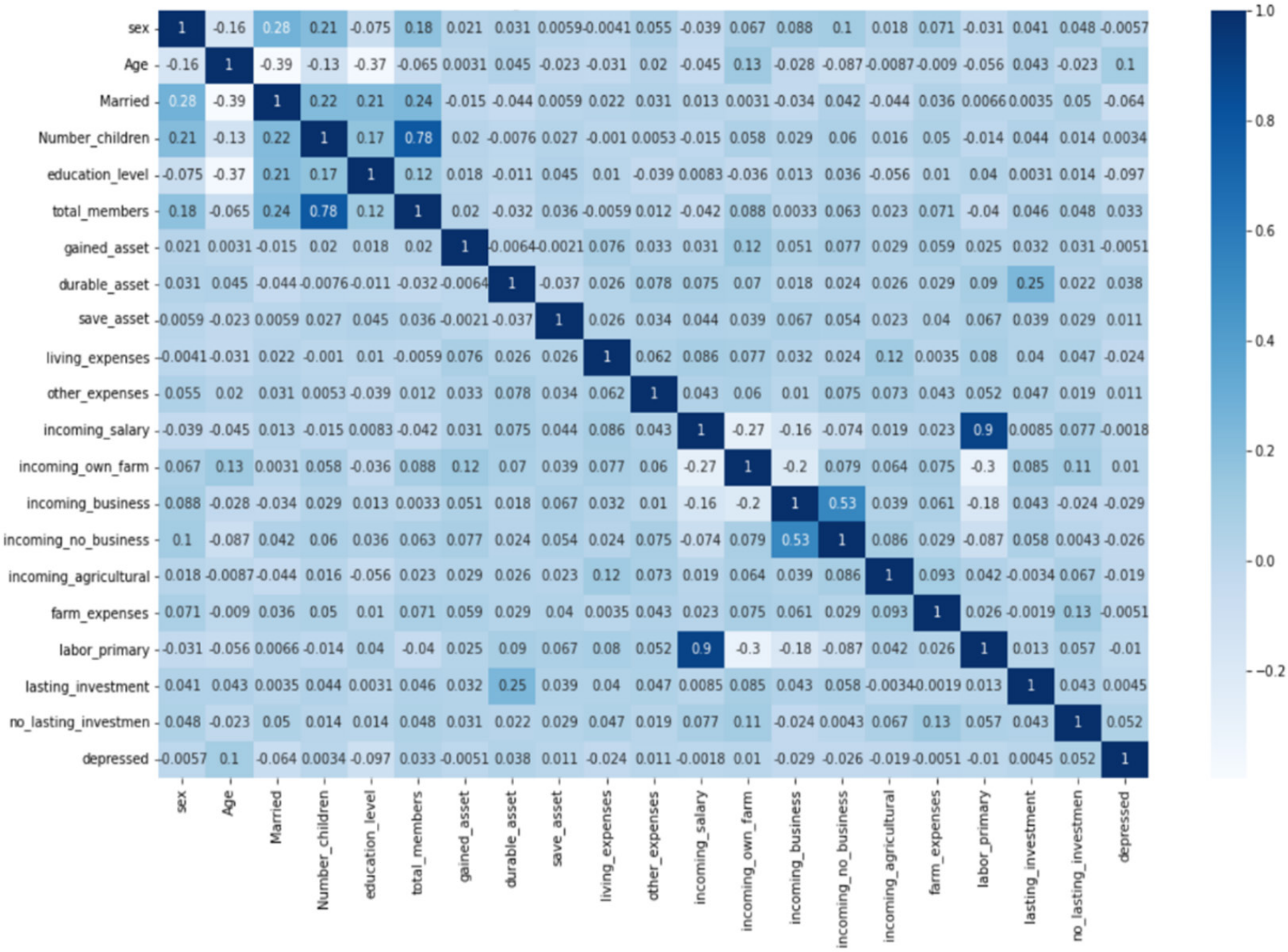

Fig. 3. Correlation matrice between all features

Figure 5 is a bar plot representing distribution of depression by gender and marital status. According to the applied dataset, it can be seen that Unmarried men are more depressed than married men, contrary to women who are more depressed after marriage. Additionally this graph indicates that male patients benefit more from marriage than female patients to avoid having depression.

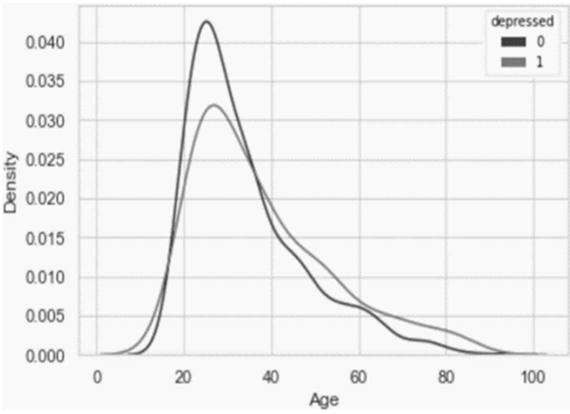

Fig. 4. Depressed and non-depressed individuals by age distribution

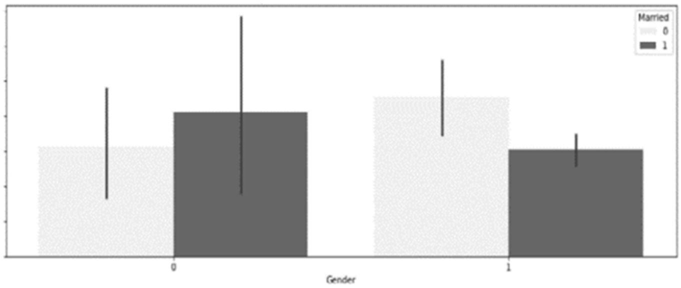

Fig. 5. Distribution of depression by gender and marital status

4.2 Results of ML analysis

For this particular section, the performance of the chosen classifier models will be evaluated using a variety of lenses. All the above classification algorithms have been used with ten cross-validation procedures across the dataset. Data have been divided into training data (80%) and test data (20).

The various cross-validation performance metrics have been benchmarked in order to assess the algorithm with the highest performance in predicting depression occurence. Table 4 highlights all performance measures of the used classification algorithms for instance, SEN, SPE, ACC, and F1-score.

Table 4. Comparison of all the algorithms

Algorithms	ACC%	SEN %	PR %	F1-Score %	Correctly Classified Instances	Incorrectly Classified Instances
LR	83.32	100	85	92	121	20
SVM	83.32	100	85	92	121	20
KNN	83.17	99	85	92	121	19
RF	80.76	98	86	91	119	19
NB	80.76	95	86	90	114	18
DT	71.39	78	84	81	94	15

5 DISCUSSION

We can notice from Table 4 that the LR and SVM achieved the highest classification ACC among All algorithms, reaching a 83.32% score. The next most appropriate algorithm to use is the k-NN, with 83.17% ACC, followed by RF and NB, which yielded a score of 80.76% ACC, and lastly, the DT algorithm, which obtained 71.39% ACC. The same ranking of the algorithms was obtained for the PR, SEN, and F1-score criteria, wherein LR, SVM shared first place with a 85% PR, 100% SEN, and 92% F1-score followed by KNN with 85% PR, 99% SEN, and 92% F1-score, whereas they are low for all other algorithms. The correctly and incorrectly classified instances were also presented in the same table. It can be seen that the algorithms LR and SVM achieved the same numbers of correctly and incorrectly classified instances with 121 and 20 instances respectively. Also, the k-NN algorithm has 122 correctly classified instances and 19 misclassified instances, followed by RF and NB. Lastly, the DT had the lowest number of correctly classified instances as well as the most misclassified instances. So, according to the results obtained, which are shown in Table 4, LR and SVM are the ML algorithms that outperform other classifiers with respect to ACC, SEN, and PR; in classifying depression dataset. In summary, SVM and LR was able to show its power in terms of effectiveness and efficiency based on accuracy and recall. Compared to a good amount [1], [14] of research found in literature that compare classification accuracies of ML algorithms, our experimental results make the highest value of accuracy (83,32%) in classifying depression dataset. The results of our study have implications for clinical practice, as they suggest that LR and SVM algorithms could be used as a complementary tool to aid in the diagnosis and prediction of depression.

6 CONCLUSION AND FUTURE SCOPE

Depression is the most common mental disorder, and it is a vast area of research with many applications in both medicine and psychology. Using socio-demographic variables in predicting depression assists also the physician in detecting depression at the earliest stage possible. The proposed models can be applied by counsellors, psychologists and universities to forecast depression which can be used to decrease the impact of this disease and assist individuals to live a better life. However, the dataset used in this study was obtained from Kaggle and may not be representative of the general population. Additionally, the dataset does not include clinical assessments or other relevant variables that may impact depression diagnosis. Moreover, we only tested a limited number of supervised ML algorithms and did not explore the potential of unsupervised learning or deep learning algorithms. Lastly, we only used cross-validation to evaluate the performance of the models and did not perform an external validation on an independent dataset. Future work should focus on addressing these limitations by conducting external validation, exploring the potential of unsupervised and deep learning algorithms, investigating the interpretability of the models, and conducting longitudinal studies to assess the effectiveness of using ML algorithms for early detection and intervention of depression.

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