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PAPER

Depression Prediction Using Enhanced Machine Learning Pipeline

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ABSTRACT

Depression is a common mental health problem that has a big impact on a person's mood, conduct, and ability to function in general. Existing studies have problems while dealing with a large number of features and selecting suitable algorithms at different stages of model development. However, current complex systems are very difficult to understand and use by doctors. The objective of this study is to propose suitable feature extraction and classification models to predict depression that are both cost-effective and easy to understand. The study concludes that the most important features were contentment with the surroundings, financial stress, sleeplessness, anxiety, and psychological issues such as conflict, abuse, and feeling inferior. The findings suggest that Boruta with logistic regression (LR) had the best accuracy of 93.3%, which is better than existing methods.

KEYWORDS

learning, feature selection, synthetic minority oversampling technique

1 INTRODUCTION

Depression is a serious mental illness that makes it hard for people to do everyday things. It affects their mood, their ability to think clearly, and their general health. If you don't get help, it might have serious effects, perhaps death. The World Health Organization [1] says that 3.8% of the world's population suffers from depression. The greatest rates of suicide are among those aged 25 to 34 and 80 to 84. In lower- and middle-income nations, almost 75% of people with depression don't get the help they need. This is mostly because of stigma, not being able to go to a doctor, and the high expense of therapy. Early identification and management are very important for slowing down the course of depression.

The future of humanity is progressing quickly with the introduction of new innovative technologies [2, 3]. Machine learning (ML) is also considered one of the key factors of modern innovative technologies, driving advancements among different domains. ML has become a useful tool in many areas such as scientific research [4],

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forecasting [5], sentimental analysis [6, 7], network traffic detection [8], sign language alphabets [9, 10], and medicine.

But it hasn't been used much in mental health because people are worried about how complicated and hard ML models are to understand. ML makes diagnoses far more accurate, but the fact that the models aren't always clear makes it hard for doctors to use them in a lot of cases. The goal of this project is to solve these worries by creating a low-cost and easy-to-understand ML system to predict depression of this strategy is to close the gap between modern ML techniques and their implementation in clinical settings with little resources. This will help with early detection to stop mental health from progressing further.

Even while more people are becoming aware of mental health problems, especially in the 25–45 age range, mental health services are still not getting enough money and are hard to get to in many areas of the globe. The COVID-19 epidemic has made things worse, making mental health problems even more common [11, 12]. ML might change the way we find and treat depression by making diagnoses more accurate, but it is not yet widely used in clinical settings. The models are complicated and hard to understand, which is why many are hesitant to use ML in clinical practice [13]. A lot of research has been done on certain groups of people, such as women who have just given birth or older people, but not much has been done on how these findings apply to the entire population [12, 14, 15]. Therefore, the objective of this study is to propose suitable feature extraction and classification models to predict depression that are both cost-effective and easy to understand. Moreover, the study's novelty lies in feature extraction and model comparison.

2 LITERATURE REVIEW

This section brings together the most recent research on finding depression, with an emphasis on ML algorithms, risk factors, and ways to choose features. It discusses several scales that are used to measure depression, lists important sociodemographic, lifestyle, and psychological risk factors, and talks about how ML models might be employed. Also, the research gaps, methodological issues, and limitations in present research are pointed out, which sets the scene for the creation of a cost-effective and easy-to-understand ML model for analyzing depression.

2.1 Scales used in depression

Many different scales have been used to measure depression, each with its own function in research and therapeutic contexts [15–18]. The Patient Health Questionnaire-9 (PHQ-9) is a common way to determine how bad someone's depression is, from none to severe. It may be used by people of all ages, from teens to older individuals [19]. It is a main tool for finding depression since it is free and easy to use. The Beck Depression Inventory (BDI) is another well-known instrument that measures the severity of depression but costs money to use [20]. The Center for Epidemiologic Studies Depression Scale (CES-D) and the Geriatric Depression Scale (GDS) both check for depression. The CES-D is more typically used with younger people, while the GDS is more often used with older people [19].

The Burns Depression Checklist (BDC) was created by [21]. It is not as well-known as other depression checklists, but it is a full 25_item checklist that includes emotional, physical, and behavioral symptoms of depression. The BDC has been shown to be reliable, but it isn't used very often in ML-driven research. This shows that there is a chance to utilize it more in automated depression identification [22]. These tools have been tested in clinical settings, but the fundamental problem is that they rely on subjective self-reporting, which may be affected by how ready the person is to provide personal information. ML algorithms may help these scales by giving objective, data-driven evaluations that might make them more accurate and less biased by people [23, 24].

2.2 Common risk factors associated with depression

To build good ML models, it's important to know that depression is a complex condition. A mix of sociodemographic, lifestyle, and psychological variables might affect depression.

Sociodemographic characteristics. Many studies show that women of all ages are more prone than men to be depressed. This is because of a mix of biological, social, and psychological variables [25, 26]. Many people think that hormonal changes and stressful experiences in life, such as traumatic occurrences, are to blame for this difference [27, 28]. However, a lot of research just looks at descriptive statistics and doesn't do extensive association testing. This makes it hard to determine what causes these gender disparities [29, 30] also varies a lot from place to place. Shorey et al. [31] did a systematic review and meta-analysis that showed that Asia, Africa, and the Middle East had the greatest incidence of depression. This is typically because of differences in income levels in lower- and middle-income nations. This study is in line with global health statistics that say these areas don't have enough access to mental health care, which makes the mental health issue worse [32].

The COVID-19 epidemic has had a huge effect on the number of people who are depressed. Gasteiger et al. [33] observed that young individuals and those who were more likely to have COVID-19 had worse mental health during the pandemic. Their research looked at associations using linear regression; however, it didn't have enough assessment measures, which made the conclusions less reliable. This shows that we need stronger, ML-based models to forecast depression, especially when there are global crises [33]. Agyapong et al. [34] also show how education levels, job satisfaction, and family stress might affect depression. People who go to college are more likely to be stressed and depressed, particularly while they are in school [35]. Low job satisfaction, especially among teachers, also leads to bad mental health because of a heavy workload and a lack of support from management [34]. These sociodemographic characteristics are quite important for predicting depression, yet most ML research doesn't look at them [34].

Lifestyle factors. To understand depression, you need to know about lifestyle variables. Studies have shown that using technology, especially too much screen time and social media, may make people feel alone and worsen their mental health, especially teens [36]. But these results don't include any ML methods, which might help us understand the link between technology usage and sadness in more detail cite [36].

Haque et al. [37] observes that physical health problems, including sleeplessness and long-term illnesses, have also been connected to depression. ML algorithms such as random forest (RF) and XGBoost have shown promise in reliably diagnosing depression based on lifestyle characteristics, attaining high performance [37]. However, these results aren't as useful for other groups of people since the study was only done on kids and teens. Kim [38] also found that smoking and not eating enough are two other lifestyle variables that might have a big effect on depression, especially in women. These characteristics, together with stresses such as job and family pressure, are quite important for predicting depression, yet much ML research doesn't pay enough attention to them [38].

Psychological factors. There are a lot of studies on depression that talk about psychological variables, including hiding your feelings and thinking about killing yourself [37]. Depression makes it hard to show your feelings, which may cause problems in relationships and make your mind work harder. To look at not just emotional and cognitive characteristics but also behavioral patterns that show signs of depression, we need more powerful ML algorithms [37]. Another important area of study is the link between anxiety and depression. Research shows that having anxiety as a child makes it more likely that you will develop serious depression as an adult [39]. But studies that looked at particular groups, including those who had strokes, have not given us much information about how these psychological characteristics affect people in general [38].

2.3 Feature selection methods

Feature selection is very important for making ML models work better since it makes them less complicated and stops them from overfitting. The Boruta algorithm is becoming more popular since it can find essential characteristics using random forest-based methods [37]. Research such as Zulfiker et al. [21] has shown that Boruta is better at predicting depression than other approaches. But a lot of research that employs decision trees still doesn't use the right features, which makes the models too complex and less accurate [40]. SelectKBest and Mutual Information, on the other hand, are more advanced strategies to choose the most important characteristics, which may make models work much better [21, 40].

Using Gini impurity to choose features, especially in decision tree-based models, has become more popular in predicting depression. For example, Park et al. [41] found that Gini impurity helps find important features such as social support and sleep quality, which are important indicators of mental health [41]. Some examples of ML algorithms for finding depression include support vector machines (SVM), RF, K-nearest neighbors (KNN), and Naïve Bayes. Each model has its own capabilities; however, RF is usually the best at managing unbalanced datasets [42]. However, there is a big gap in adopting these models for the entire population since most research has only looked at certain categories, including women who have just given birth or older people [38]. Also, even though artificial neural networks (ANNs) and convolutional neural networks (CNNs) have been used a lot in clinical research, especially for image processing, they haven't been used a lot to find depression [43]. ANN-based models work well, but they are hard to understand, which makes it hard to use them in real-life clinical situations.

Even while ML has a lot of potential to help find depression, there are still a lot of problems to solve. Getting permission and other ethical issues are big problems for research that uses sensitive data [44]. Also, sampling bias and model overfitting may make results untrustworthy, especially when utilizing small, homogeneous datasets [45]. The dearth of good data and datasets that aren't balanced also make it hard to build strong models. To fix data imbalance and make models better at predicting, people [21]. But there is still a lot more research to be done on how to use synthetic minority oversampling technique (SMOTE) and other data preparation approaches to find sadness. Also, a lot of research hasn't used the right assessment measures, which makes their conclusions less reliable [33]. Researchers in the future will have a hard time comparing and building on previous work since there aren't enough thorough assessment techniques. This slows down the progress of ML in finding depression [33].

3 METHODOLOGY

3.1 Dataset description

This study employed a secondary dataset that was initially gathered by Zulfiker et al. [21] and was downloaded from GitHub. To follow data privacy rules, the data has been anonymized. The dataset is for the general population of Bangladesh and comprises 30 sociodemographic, physical, psychological, and stress-related characteristics that might help predict depression [21].

3.2 Data analysis

We used Python (via Jupyter Notebook) for ML and data processing and Tableau and Excel for showing the data. There are several processes in the approach, including preparing the data, choosing features, implementing the model, and evaluating it. The next sections go into more depth about these stages.

Data preprocessing. Some categorical variables still need to be changed into numerical data for ML analysis, even if the dataset has previously been cleaned up and missing data has been removed. The Python function df[col_name] will be used to change the categorical variables in this investigation. astype('category'). cat.codes gives each category a number code. For instance, gender will be classified as 0 for male and 1 for female, making sure that all attributes are numbers that ML algorithms can use.

Synthetic minority oversampling technique. There are more people in the dataset who are classed depressed than non-depressed. The SMOTE is used to fix this [46]. SMOTE generates fake samples by utilizing the K-nearest neighbors' approach to balance the dataset so that the ML model doesn't favor the majority class. The SMOTE technique makes a dataset fairer by choosing a participant from the minority class and generating synthetic data points based on its closest neighbors [47]. SMOTE makes models more accurate, but be careful when using it before feature selection since certain feature selection approaches presume that samples are independent [46].

Feature selection analysis. Choosing the right features is an important part of making a good ML model. The dataset is split into two parts: 70% for training and 30% for testing. Feature selection is done on the training data using the following methods:

- **Boruta:** We utilized the Boruta method and RF [48] to choose the most important attributes. Boruta uses an iterative procedure to find key characteristics by comparing the relevance of original features to those of shadow attributes. Features that always do better than the shadow traits are kept, while others are thrown away. This method helps reduce noise and makes the model more reliable [37].
- **Chi-Square Test:** Using the SelectKBest feature selection approach, the Chi-Square test was used to see how dependent each feature is on the target variable.
- **Mutual Information (MI):** We utilized MI to figure out how dependent the characteristics are on the target variable. MI is good at finding nonlinear correlations between variables. This makes it a good choice for predicting depression, because there are many complicated interactions. It figures out how much information the features and target share, and larger MI values mean that the dependencies are stronger [37].

- **Gini Impurity:** Random forest models will utilize the Gini Impurity approach, which is often used in decision tree algorithms, to figure out how important each feature is. It checks the "impurity" of data splits by figuring out how likely it is that they will be misclassified. Features with lower Gini impurity values are thought to provide more information [49, 50]. We will add this approach to RF models to make feature selection better.

Hyperparameter tuning. Hyperparameter tuning finds the optimal set of parameters to improve the performance of a model. We will utilize the Grid Search technique to fine-tune the hyperparameters. This approach lets us search over a set parameter grid to find the best values. As shown in Table 1, the following settings will be adjusted for each ML model [51].

Table 1. Parameters and values used in GridSearchCV per ML model for this study

ML Algorithms	Parameters	Values
Logistic Regression	C	[0.01, 0.1, 1, 10, 50, 100]
	Penalty	['l1', 'l2', 'elasticnet', None]
	Solver	['liblinear', 'saga', 'lbfgs']
Random Forest	N_estimators	[10, 20, 25, 50, 75, 100, 125, 150]
	Criterion	['gini', 'entropy', 'logloss']
	min_samples_split	[10, 20, 50, 100]
	min_samples_leaf	[10, 20, 50, 100]
	max_features	[1,'sqrt','log2']
Artificial Neural Network	Epochs	[10, 25, 50, 75, 100]
	Batchsize	[10, 25, 50, 75, 100]
	Optimizer	['adam','sgd','rmsprop']
Support Vector Machine	C	[0.01, 0.1, 1, 10, 100]
	kernel	['linear', 'poly', 'sigmoid']
	Degree	[2, 3, 4]

Each algorithm will go through grid search and five-fold cross-validation to find the optimum hyperparameters. This will make sure that the model works well and lower the chance of overfitting.

3.3 ML algorithms

We used several ML techniques to see how well they can predict depression.

Logistic regression. Logistic regression (LR) is great for predicting binary outcomes, such as whether someone is depressed. It works well when the dependent variable can only take on two values. The LR formula shows how the dependent variable and the independent variables are related.

Random forest. The random forest uses several decision trees to determine what kind of depression someone has. RF lowers the chance of overfitting relative to single decision trees by averaging predictions from several trees. This makes the model more accurate. RF works well with data that has a lot of dimensions and is often used for classification jobs.

Artificial neural network. Artificial neural networks are good at recognizing and classifying complicated patterns because they are built like the human brain. ANNs may find nonlinear correlations between features, which makes them good for predicting depression, where interactions are typically complicated. This study will employ a feed forward neural network (FNN), which is a simple kind of ANN that works well for binary classification tasks.

Support vector machine. Support vector machines are strong classifiers that locate the best hyperplane to divide classes in space with a lot of dimensions. SVM is very good at finding a compromise between accuracy and repeatability, which makes it a good choice for this study's categorization of depression.

Evaluation metrics. We utilized a confusion matrix to figure out how well ML models are doing by looking at measures such as accuracy, precision, sensitivity, specificity, and F1_score. These measures will provide a full picture of how well each model can find depression and reduce mistakes.

4 RESULTS

This demonstrates the outcomes of looking at the dataset, with an emphasis on demographics, feature selection outcomes, and how well ML models worked. We look at the findings in different configurations to see how well the model can predict depression and find the most important parameters linked to this condition. We used the BDC to see whether the people who took part were depressed. A score of 10 or above on the checklist indicated that the person was depressed. There were 604 people in the sample, and 397 of them (66%) were depressed.

Most of the people who answered were men (75%), and over half (49%) were between the ages of 21 and 25. Many participants (73%) were students, and 85% were single. We got these numbers before we used SMOTE to make the dataset more even. There were disparities in depression between men and women. 64% of men and 70% of women were considered depressed. Age was also a big factor. The younger group (21–25) had the most cases of depression, whereas the older groups had less participation, notably those 31 and older. There were no individuals in the 36–40 and 51–55 age groups who were not depressed (see Figures 1 and 2).

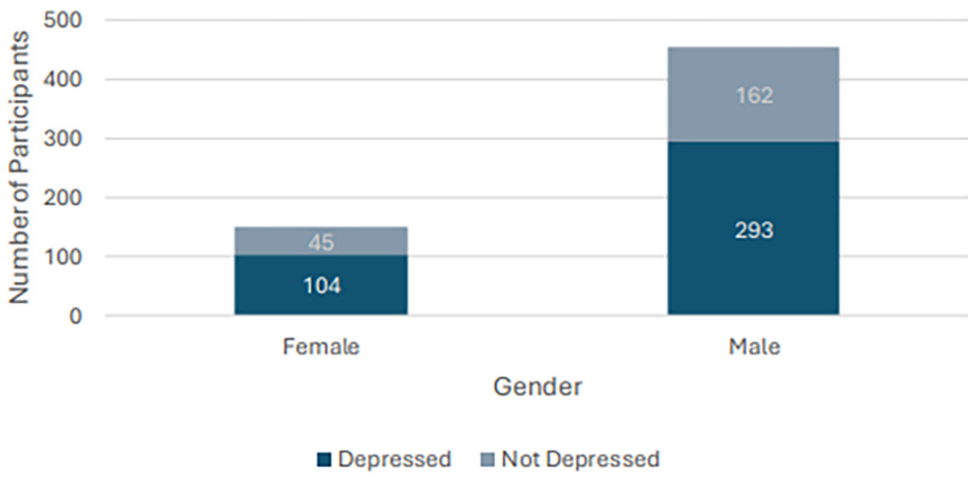

Fig. 1. Distribution of depression status between genders

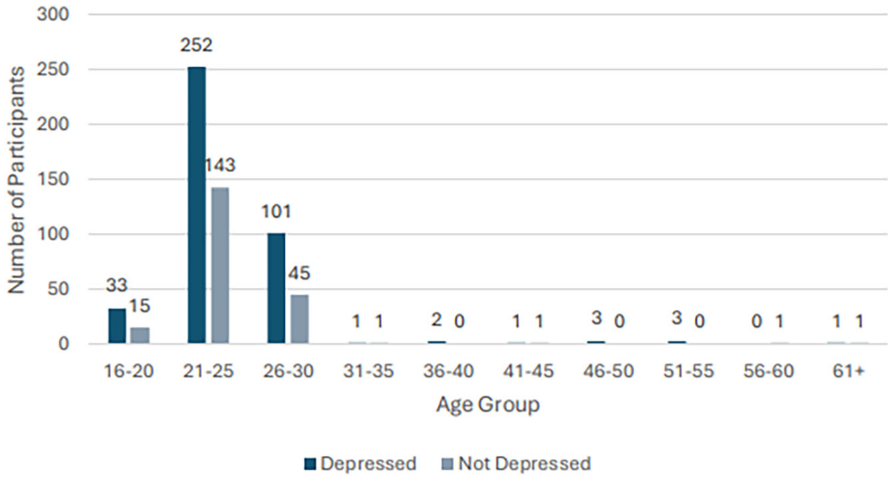

Fig. 2. Distribution of depression status per age group

Moreover, half of the people who took part (52%) had finished university, and 86% of those with secondary school certificates (SSC) were classed as depressed (see Figure 3). This makes sense since most of the people who took part were between the ages of 21 and 25 and had not yet started working. Profession was also a factor. Students (73% of respondents) were the most afflicted by depression, followed by those in other professions, save for government workers (see Figure 4).

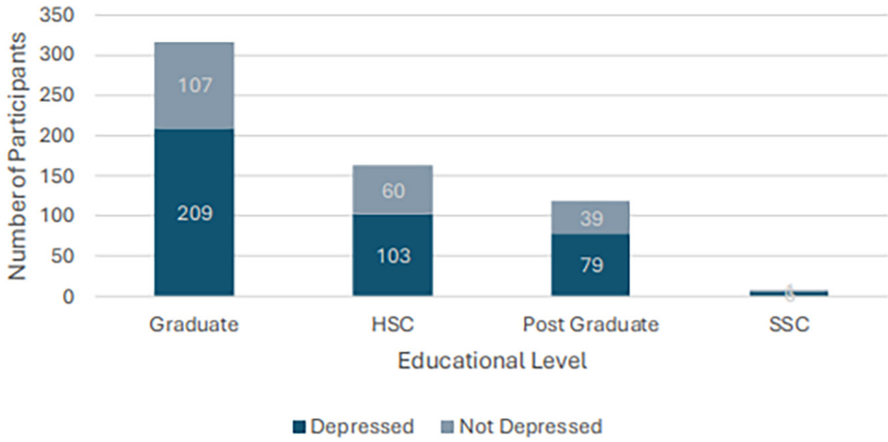

Fig. 3. Distribution of depression status per educational level

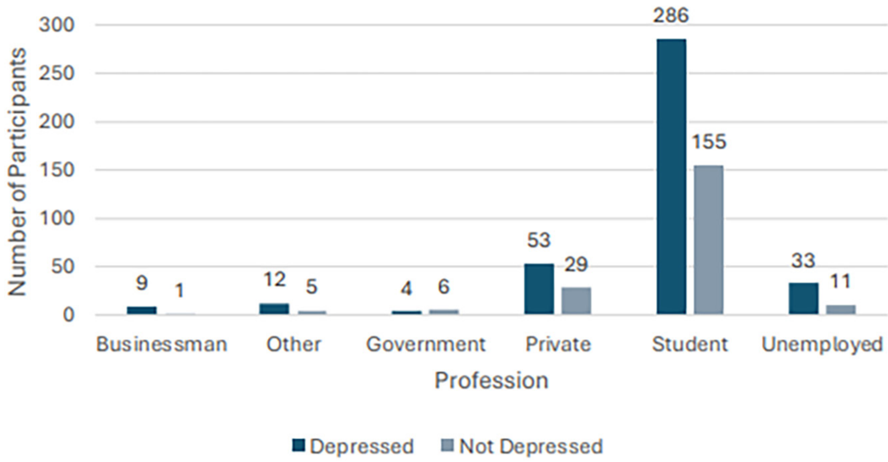

Fig. 4. Distribution of depression status per profession

In terms of marital status (see Figure 5), 66% of unmarried individuals were depressed, whereas only 63% of married people were. All three of the divorced people in the sample were classed as depressed.

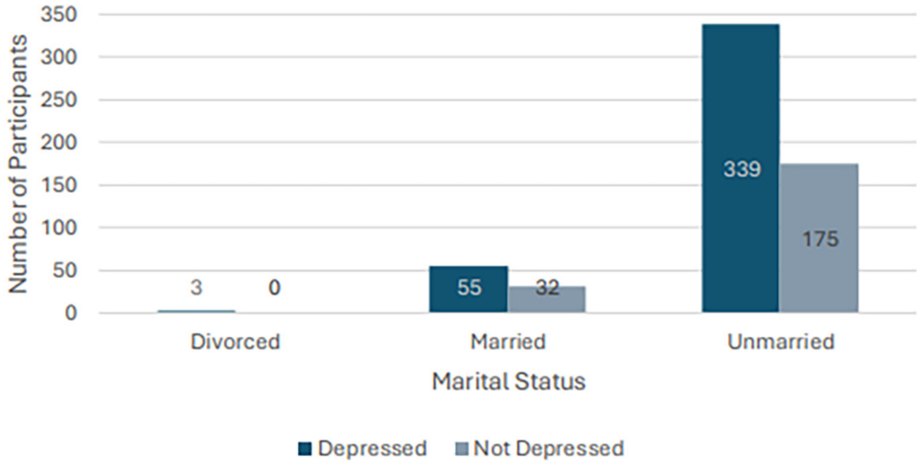

Fig. 5. Distribution of depression status per marital status

Where people lived also influenced sadness; 51% of city inhabitants and 57% of rural residents were depressed (see Figure 6). This means that depression is more common in rural regions, yet those who live in cities still have high rates of depression.

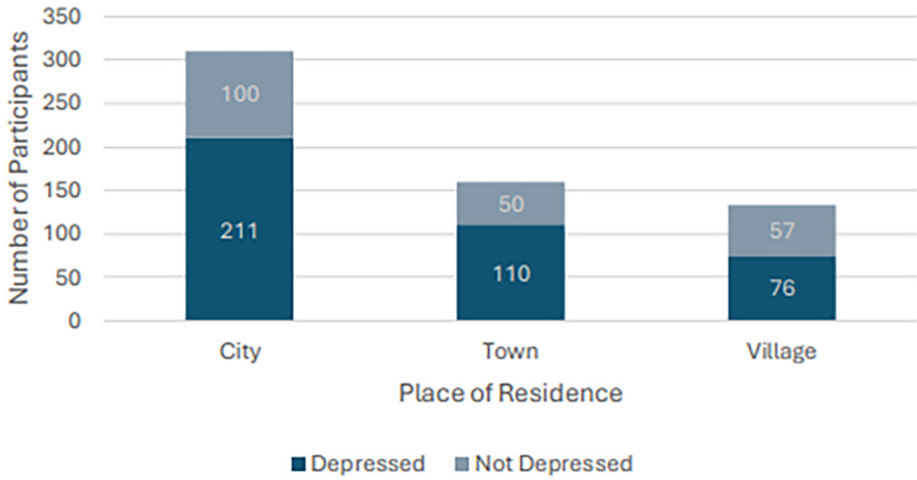

Fig. 6. Distribution of depression status per place of residence

We employed many feature selection approaches after using SMOTE to balance the dataset. These included Boruta, Chi_Square (χ^2), MI, and Gini Impurity. The research showed that several psychological characteristics, including anxiety, deprivation, abuse, feelings of inadequacy, and issues with relationships, were the best predictors of depression across all feature selection approaches. These characteristics always came up as important predictors in all techniques, which shows that they are important for predicting depression.

- Boruta identified several significant factors, including environmental satisfaction, academic satisfaction, financial stress, insomnia, and anxiety.

- Chi-Square emphasized financial stress, insomnia, and anxiety as key contributors.
- Mutual Information and Gini Impurity also highlighted similar features, such as feelings of being lost and suicidal ideation.

We evaluated several ML models after choosing the features to see how well they could predict. With all features, RF achieved the highest accuracy at 91.21%, while SVM had the lowest accuracy at 87.87%.

The Gini Impurity technique and LR together gave the most accurate results at 92.05% when tested with the top 10 characteristics. In most circumstances, LR did better than the other models. The only time it didn't do better was when Chi-Square was utilized, when RF did the best. The 11-feature model, which used Boruta and LR, had the greatest overall accuracy at 93.31%. This result was better than the one by Zulfiker et al. [21], which got 92.56%. When 12 features were used to test it, Boruta with LR once again had the best result at 92.89%. MI with LR had the greatest accuracy at 92.05% for 13 characteristics. ANN with Boruta, on the other hand, did the worst, with a score of 84.94%. Gini Impurity with RF had the best accuracy at 92.47% with 14 features. Chi-Square with LR and SVM had the lowest accuracies. In most feature selection situations, RF always did better than LR. But LR with Boruta and Gini Impurity did better overall. ANN and SVM gave different outcomes, and most of the time, the accuracy was lower. Lastly, we put up a table that shows the performance metrics of the best models for each feature selection setting (See Table 2). The 11-feature model that used Boruta with LR had the best accuracy and precision, as well as very high sensitivity and specificity scores. These results show that Boruta with LR is a dependable and easy-to-understand model for identifying depression.

Table 2. Performance comparison of feature selection methods and ML models

Features	Feature Selection	ML Model	Accuracy	Precision	F1-Score
All	None	RF	91.21%	92.56%	91.43%
10	Gini	LR	92.05%	94.87%	92.12%
11	Boruta	LR	93.31%	95.76%	93.39%
12	Boruta	LR	92.89%	94.96%	93.00%
13	MI	LR	92.05%	95.65%	92.05%
14	Gini	RF	92.47%	95.69%	92.50%
15	MI	RF	91.21%	91.87%	91.50%

5 DISCUSSION

5.1 Demographics

The demographic data gives us a lot of information on how common depression is in different groups, with big variances shown in age, gender, marital status, career, and where people live. Figures 2 to 6 illustrate that depression was common in all demographic groups. There is a link between gender and depression: 70% of women and 64% of men are categorized as depressed. Gender was not one of the most important factors found by the feature selection techniques, but this conclusion validates previous research, such as Cho et al. [25] and Handing et al. [26], which found that women are more likely to be depressed. Zhao et al. [52] said that this higher risk was due to genetic and environmental variables that are only present in females, such as changes in hormones and social pressures [26, 52]. The survey also indicated that a lot of young people (ages 21 to 30) were depressed. In fact, 64% of those ages 21 to 25 and 69% of those ages 26 to 30 were classed as depressive (see Figure 3). This fits with what Gasteiger et al. [33] and Thapar et al. [53] found in earlier research, which shows that young people encounter problems that are different from those of older individuals, such as dealing with chronic pain, bullying, and a family history of depression. Young people who are depressed may have big problems with their social, academic, and work lives, therefore, it's important to deal with these difficulties as soon as possible [33].

When it came to marital status, the data revealed that all of the divorced participants were sad (see Figure 6), even though there were only three of them. Hald et al. [33] found that divorce is linked to increased incidence of depression, but since this study had a small sample size, it's hard to say for sure what the link is between divorce and depression. The research also revealed that 63% of married people were depressive, which is in line with what Whisman et al. [54] observed: marital problems may make married people quite unhappy [54]. The data also indicated some intriguing trends based on where people lived. Urban inhabitants were more likely to be depressed (68%) than rural residents (57%) (see Figure 6). Xu et al. [55] also found that urbanization is linked to a greater incidence of depression, particularly in developed nations. These results are in line with that. But because of cultural and economic differences, the effect of urbanization on mental health in Bangladesh may be different. More study would be needed to confirm this link.

5.2 The model's features

The characteristics chosen for this study are in line with what has already been found in depression studies. For example, both Boruta and other feature selection approaches found that environmental happiness and academic satisfaction were important factors. Schorr et al. [56] observed that being unhappy with the surroundings, especially when it comes to social activities, might lead to sadness, especially in older people. In this study, it was important for younger people, which shows how important it is to be sociable to avoid depression.

Another major factor was academic satisfaction, which is in line with what Deng et al. [35] and Remes et al. [57] found: that poor academic achievement and excessive academic pressure may make people feel like they have failed and have low self-esteem, which can lead to depression. The results also imply that kids who have these problems may have trouble sleeping, focusing, and dealing with stress, which makes their depression worse. The research also indicated that financial stress was a major factor, which is in line with Frankham et al. [58], who discovered a substantial link between financial pressure and depression. Guan et al. [59] also said that those with lower earnings are more likely to be depressed. The findings of this research show how important it is to include financial health in a complete approach to mental health [35, 58].

The findings of this study were compared to those of other studies, such as Zulfiker et al. [21], and they revealed significant gains in performance. This study's 11-feature model has an accuracy of 93.31%, which is better than the 92.56% accuracy that Zulfiker et al. [21] found. This model also did very well in terms of precision (95.76%), sensitivity (91.13%), specificity (95.65%), and F1-score (93.39%), which shows that it is quite good at predicting depression. Table 3 shows how this study's results compare to those of other research that used other ML algorithms and feature selection approaches. Our study employed Boruta with LR, which was more accurate and faster than Zulfiker et al. [21], who used 15 features with adaptive boosting and SelectKBest (chi-square). The findings show that simpler models, such as LR, may be better at making predictions and explaining things than more complicated models [21].

Table 3. Comparison of classification models and feature selection methods from previous studies

Author	Model	Feature Selection	Accuracy
[21]	Adaptive Boosting	SelectKBest	92.56%
[42]	Random Forest	N/A	79.80%
[51]	Artificial Neural Network	N/A	77.10%
[60]	ET + LGBM + RF + LR	Recursive feature elimination with cross-validation with RF	77.36%
[38]	SVM	Wrapper Method	70.00%
Our Study	LR	Boruta	93.31%

This research did better than all except Zulfiker et al. [21] when compared to other studies, including Priya et al. [42], Abdallah et al. [61], and Nguyen and Byeon [60], which employed different ML approaches and ways to choose features. The fact that this research utilized a simple model (LR with Boruta) shows that it works well for predicting depression, even without complicated algorithms or sophisticated feature selection [21, 42, 60]. The findings of this research have important effects on how to find depression early. The LR model did very well, even though the dataset was unbalanced. This was because SMOTE was used to balance it. This means that LR is a good and quick way to find depression in places where resources are limited. LR is very simple to use and understand, so doctors and researchers may use it without needing a lot of computer power [62],

The results also imply that employing simpler, easier-to-understand models such as LR may provide results that are just as good as those from more complicated models. This is helpful in clinical situations where it's important to be able to comprehend and explain results to patients and doctors. This method could make ML models more acceptable in psychiatric treatment, where openness is very important. The findings also show how important it is to look at sociodemographic, psychological, and environmental aspects when diagnosing depression. These results may help clinicians and policymakers create tailored treatments that concentrate on improving these aspects. For example, they might improve academic assistance for students and deal with socioeconomic and environmental stresses. The research gives us useful information, but it also has certain problems. One problem is that there aren't any quantitative factors, such as BMI and pay, that have been linked to depression in other research [63, 64]. Adding these kinds of factors could make the model more reliable. Another problem is that the sample size is limited compared to the whole population of Bangladesh. We used SMOTE to even out the data, but a bigger sample size would give us findings that are more likely to be true for the whole population and lower the chance of sampling bias. A bigger and more varied sample might also give us a better idea of how depression affects people of various ages, races, and backgrounds [63].

6 CONCLUSION

The fight against depression is still very hard for people all around the world. This research needs policymakers and doctors to help the mental health needs of people impacted. This study used several ML models and optimization methods to find the most important things that cause sadness and make the system better at predicting it. The research shows how useful ML models may be in medicine, especially for finding depression in a way that is easy to understand, follow, and repeat. The suggested approach did better than other techniques when it came to assessment metrics, showing that it is effective and efficient in finding depression. Also, this research stresses the practical usage of simpler, more reliable ML models, which makes them easier for doctors to utilize, particularly in places with fewer resources. In addition, the classification models evaluated (e.g., LR, RF) to give readers a clearer picture of the experimental design. This study may help policymakers make it easier to get mental health care by providing a foundation for future research and applications. This might lead to changes in laws and regulations that make it easier for people to get mental health services. Depression detection through explainable AI can assist clinicians in timely intervention and personalized care.

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