SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V10I5P106

Volume 10 Issue 5, 60-68, May 2023


*Original Article*

# Analysis of Undergraduate Student's Knowledge of Self-Medication Practice using Machine Learning Algorithms

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Received: 05 March 2023 Revised: 13 April 2023 Accepted: 07 May 2023 Published: 29 May 2023

***Abstract -*** *Self-medication (SM) is a medicinal product used to treat symptoms or self-medicate disorders identified by oneself. Overusing the medication recommended by a medical doctor for oneself or other family members (particularly when considering a child or an elder) falls into the description of SM. Treating medicine for oneself without specialist guidance might cause many side effects like prolonged disease course, drug resistance and complications. Even though informed SM is one method to decrease healthcare costs, inappropriate self-treatment poses different risks involving the recurrence of symptoms, drug resistance, drug side effects, etc. The study aims to examine the pervasiveness of SM in undergraduate students worldwide through a meta-analysis and systematic review of the study published on SM. A self-administered survey will collect data on demographic variables and practice SM to perform this study. The data is collected among undergraduate students from Aldayer University college, Jazan University, and KSA under three disciplines: English, maths, and nursing. The study aims to assess undergraduate students' knowledge regarding SM, identify drugs that students have taken without a prescription in the last six months, identify the reason for SM, identify sources of information about SM, and detect the sources of drugs utilized by students for SM. One hundred eighty samples were selected by purposive sampling per inclusive criteria at L Aldayer University College, Jazan University, KSA. The total number of samples is 180, of which 60 are collected from each discipline. In addition, machine learning-based support vector machine models can be used to generate predictive models to identify which studies are taking high SM. The experimental results stated that nursing college studies involve more SM practices than other undergraduate students.*

***Keywords -*** *Machine learning, Self-medication, Healthcare, Medication.*

## 1. Introduction

SM, an essential and significant element of self-caring, is described as "choosing and implementation of pharmaceutical/medicinal items encompassing conventional and herbal items by a person to diagnose self-identified diseases or indications [1], or the irregular or sustained employment of a drug suggested by a medic for long-lasting or frequent illness or sings". Though SM is carried-out globally, the practice may be in more significant numbers in emerging nations [2]. Several aspects influence SM, a few of which are socioeconomic, for example, health consciousness, economic standing, level of education, reach to medical knowledge, etc. Additionally, health sector amenities, healthcare enhancements, and drug reach [3]. Advancement among individuals' typical intellectual and educational standards, economic standing, and advancement in techs like the internet and associated platforms endorse SM globally [4]. The WHO has promoted accountable SM for diagnosing and prohibiting symptoms/signs that do not need medical counselling [5]. It is a cost-effective substitute for diagnosing prevalent diseases. It may be crucial in nations like Nepal, where the pharmaceutical reach is quite challenging, and there exists a scarcity of medics, particularly in remote areas [6]. However, the exercise of self-treatment should be assisted by impartial pharmaceutical data given to individuals to prevent health threats [7].

SM comes with both merits and challenges. Accountable SM can prevent rare pharmaceutical sources from being exploited in less demanding situations [8], mitigate the threshold on healthcare sectors, and reduce the price and time one utilizes in reaching healthcare sectors for trivial signs [9]. However, improper SM can lead to substantial severe damages, e.g., prolonged delay in getting relevant medical

assistance, failure to diagnose or conflict in self-diagnosing [10], delay in reaching suggested medical prescription, failure to explain present SM to the assisting medic, which leads to the threat of double medication and hazardous interaction [11], improper period/duration in the usage of the drug, the threat of reliability and misuse, etc., [12]. SM can provide various merits to the patients that encompass rapid reach to diagnosis, freedom in lessening signs, cost-effectiveness in reaching the medical sector and rate of visits to the medical centre [13], and also in the aspect of public, the merits comprise of preserving pharmaceutical sources, reduced leave of absence from the workforce [14, 15], reduced demand on pharmaceutical utilities, and giving more significant time of severe circumstances [16]. Nevertheless, despite its several merits, SM, particularly if unassisted, can lead to potential threats at the personal level, like wrong treatment, stern hostile results [17, 18], elevated antimicrobial confrontation, harmful diet and medical communications, and medicine mishandling and abuse [19]. Additionally, at the public level, unassisted SM may result in enhanced medication tempted ailment and public expenditures. The adverse outcomes of SM can be significantly realized in several emerging nations with restricted sources, less education level and health sector facilities, along with large populations that will neither have proper education related to treatment nor have reached knowledge, a time limit in usage and medicinal dose or aftermath reaction [20].

The study aims to examine the pervasiveness of SM in undergraduate students worldwide through a meta-analysis and systematic review of the study published on SM. A self-administered questionnaire collects information on demographic variables and practising SM to achieve this. The study aims to find a reason for SM, evaluate university students' knowledge regarding SM, identify sources of information about SM, detect the sources of drugs students utilise for SM, and recognize drugs that students have taken without prescription during the past six months. Furthermore, a machine learning (ML) based support vector machine (SVM) model was used for generating prediction models. The experimental outcomes demonstrated that nursing college educations include more SM practices than other university students.

## 2. Literature Review

Deborah Tolulope Esan et al. [21] evaluated the SM practice among private university UG students. A descriptive cross-sectional model is used in this study. A pre-tested questionnaire was self-administered to 384 UG students. With inferential and descriptive statistics like Fisher’s and chi-squared tests, data were examined and summarised. Doa'a Anwar Ibrahim and Abdulsalam Halboup [22] concentrated on the practice of SM among the health science UG students who are in paramedical or medical at diverse education levels in the city of Sana'a. A potential cross-sectional survey was validated and structured to do a sample of health science UG students in Sana'a City. Logistic regressions and Chi-square tests are the analytical techniques exploited in this study.

Marion Gras et al. [23] intended the article to define the features and prevalence of SM performances among postgraduate and undergraduate students from several departments. The author even aimed to detect determinants of unsuitable SM. Depending on a self-questionnaire of students from different circles of academics at Picardy University (Amiens, France), the author executed a descriptive, cross-sectional study. Ghada L. Elkbuli, and Rogaia A. Draidi [24] This study intends to evaluate antibiotic SM practices among pharmacy students at Libyan University. It was cross-sectional research takes place at Sabratha University among pharmacy students. An authenticated questionnaire has been used to gather relevant data for statistical analysis. Olumide Ajibola et al. [25] study aims to understand antibiotic resistance and assesses self-medicated antibiotics among community members and UG students. Utilizing a structured questionnaire, attitudes towards antibiotics, antibiotic consumption patterns, illnesses commonly treated, knowledge of antibiotic resistance and source of prescription were explored. With descriptive statistics, responses were summarized and analyzed. Sitaram Khadka et al. [26] aimed to focus on the health-seeking performance of UG medicinal students and evaluate how they deal with their diseases, including the SM practice. A total of 210 students have been chosen using a systematic sampling technique in this cross-sectional research based on the web, which takes place among UG medicinal students. Utilizing SPSS version 20, the data were analyzed. Frequency was computed for all the variables.

## 3. Materials and Methods

SM is the self-management of treatment (either behavioural or pharmacological) without a prescription from a medical practitioner. SM is a stern concern for public health that seems to be increasing in developed and developing nations. Some serious consequences of SM are the development of co-morbidities, delay in disease diagnosis, and drug resistance, sometimes leading to death. Among all age groups, adolescents are the most susceptible to SM. Specifically, students find medication information online due to their ability and higher educational level, most probably self-medicate. A reliable and precise prediction of the SM rate becomes a significant factor for health policy-makers and decision-makers to implement and design programs to prevent SM.

### *3.1. Participants and Data Collection*

This study will exploit an Institutional-based cross-sectional study design to assess the University College students at Aldair, JazanUniversity, KSA. The target population will be Nursing, English and math department

students from all levels who meet the inclusion criteria. Five Samples from each level from all disciplines were chosen using a stratified random sample method. The five samples from each level are selected using a convenient sampling technique. The questionnaire used for data collection purposes is given in Appendix.

*3.1.1. Inclusion Criteria*

- Students who have regular attendance at college and in clinical areas.
- Students from all the level from nursing English and Maths department

*3.1.2. Exclusion Criteria*

- Who are critically ill and unable to respond to the questionnaire during the data collection period will be excluded.

*3.1.3. Data Collection Method*

The data will be collected by implementing a self-administered survey.

- Part-1, student's socio-demographic data
- Part: II. Knowledge about SM, the reason for SM, type of SM and duration of SM, sources of obtaining SM

*3.1.4. Data Collection Procedure*

The descriptive research design will be selected for the study. The study will be done after obtaining ethical permission from the deanship of the research department. As per inclusion criteria, the students willing to participate and sign informed consent will be selected using stratified random sampling and a convenient sampling model. The data will be collected by employing a structured survey. The data collection period will be for three months. After collecting the data, it will be analyzed using inferential and descriptive statistics. In summary, 180 samples were selected by purposive sampling per inclusive criteria at L Aldayer University College, Jazan University, KSA. The total number of samples is 180, of which 60 are collected from each discipline (Maths, English, and Nursing).

***3.2. Data Analysis Models***

Cortes and Vapnik first proposed an SVM where the fundamental concept is to create an optimum decision hyperplane that maximizes the distance between the two sample classes on the hyperplane's sides, thereby ensuring a better generalization capability for supervised classification cases. SVM could handle smaller samples and non-linear pattern detection and be applied in different cases, like prediction and function approximation. The support vector in SVM is a few training points in the sample training dataset that are the most complex data point to be classified and closest to the classification decision-making surface. The better classification standard in SVM is attained once the distance between the points to the classification hyperplane attains the maximal value. Figure 1 illustrates the structure of SVM.

Assume a trained set $\Omega$ of vectors separated as two classes [27]. Vector is defined by a pair $(x_i, y_i) \in \mathbb{R}^n \times \{-1,1\}$, in which $n$ denotes the number of features observed for all the vectors, $x_j$ has the feature vector for $i\text{-}th$ vectors and $y_i$ Denotes two classes of $\Omega$ vector $i$ be appropriate. If $\Omega$ was linearly separable, there is $u \in \mathbb{R}^n$, $\theta \in \mathbb{R}$, and $\mu \in \mathbb{R}_0^+$ so that each vector from the class wherein $y_i = -1$ satisfy $u^T x_j \geq \theta + \mu$ and each vector in the class wherein $y_j = 1$ satisfy $u^T x_i \leq \theta - \mu$. W.l.o.g. segregating by $\mu$, the SVM Problem consisting of the hyperplane $f(x) = w^T \cdot x + b$ that optimally separates the vector during the training set. Optimality was two-fold, which supports a few vectors of 2 two classes and minimalizes the sum of classifier errors. The conventional hard margin SVM method reduces the compromise between the abovementioned two objectives, the empirical risk and the structural risk.

$$w, b, \xi min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m} \xi_i \quad (1)$$

$$s.t.\, y_j\left(w^T x_j + b\right) \geq 1 - \xi_j \; i = 1, \ldots, m, \quad (2)$$

$$\xi_i \geq 0 \; i = 1, \ldots, m, \quad (3)$$

The $n$-dimensional vector $w$ has parameters $w_j$ along with $b$, take value in $\mathbb{R}$ and characterizes the coefficient of the two parallel hyperplanes $w^T x + b = 1$ and $w^T x + b = -1$. The initial term $\frac{1}{2}\|w\|^2$ of the primary function (1) represents a structural risk; meanwhile, $\|w\|$ is double the inverse of the distance among both hyperplanes. Variable C defines how significant it is to prevent misclassification during the training dataset. Constraints (2) & (3) ensures that either vector in a class $y_j = -1$ satisfy $(w^T x_j + b) \leq -1$ and vector in the class denoted by $y_j = 1$ satisfy $(w^T x_j + b) \geq one$ or constraint (2) can be violated by the positive amount $\xi_j$, represents the deviation. The slack variable $\xi_j$ Makes the difference, including the soft margin SVM method.

Assume the two objectives, $O_1 = \frac{1}{2}\|w\|^2$ and $O_2 = \sum_{i=1}^{m} \xi_i$. As abovementioned, the objectives in SVM were maximizing distance among two parallel hyperplanes supporting the sum of the classifier error. It is easier to verify objective values. $O_1$ and $O_2$ allow us to accurately calculate both objective values, viz., the distance between 2 parallel hyperplanes determined by the parameters $w$ and $b$ and the total distance of the misclassified vector to the respective hyperplane. Consider $(w, b, \xi)$ a promising solution to SVM. Next, $\pi_1 \equiv w^T x + b = 1$ and $\pi_2 \equiv w^T x + b = -1$ denote the two parallel hyperplanes and the distance among them can be given as follows:

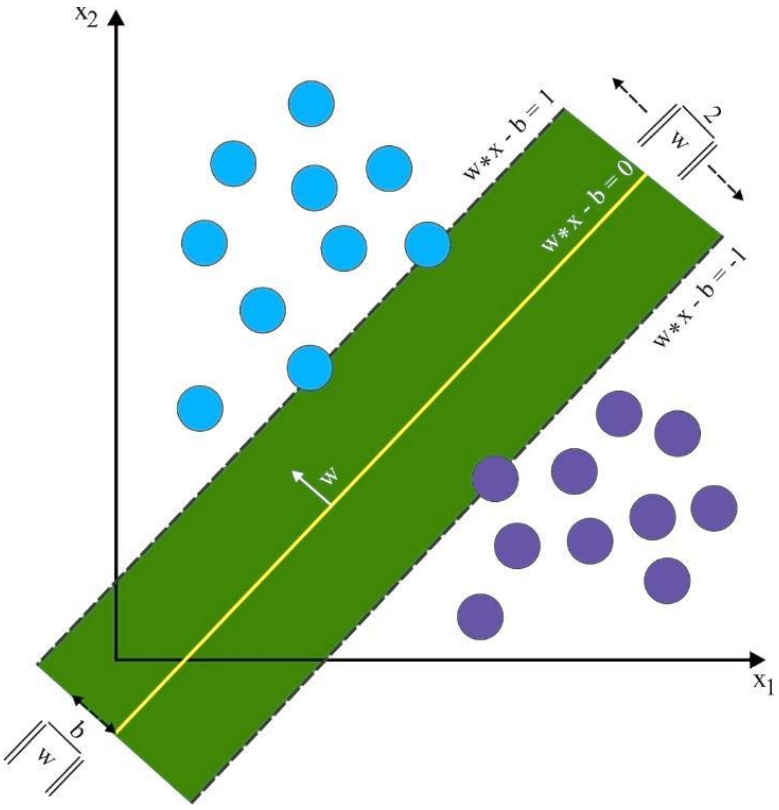


**Fig. 1 SVM hyperplane**

$$d(\pi_1, \pi_2) = \frac{2}{\|w\|} = \frac{2}{\sqrt{2O_1}} \quad (4)$$

The sum of the distance of misclassified vector is 1 and $-1$ to the hyperplane $\pi_1$ and $\pi_2$. If $\xi_i = \max\{0, 1 - y_j(w^T x_j + b)\}$, then it can be formulated as:

$$\sum_{i:\xi_i>0, y_i=1} d(x_i, \pi_1) + \sum_{i:\xi_i>0, y_i=-1} d(x_i, \pi_2) = \sum_{i:\xi_i>0, y_i=1} \frac{\xi_i}{\|w\|}$$

$$+ \sum_{i:\xi_i>0, y_i=-1} \frac{\xi_i}{\|w\|} = \frac{O_2}{\sqrt{2O_1}} \quad (5)$$

## 4. Results and Discussion

In this segment, the SM classification of the proposed model under three datasets (i.e., English, Maths, and Nursing) is given briefly. Table 1 shows the classification results of the SVM model under three datasets as a confusion matrix. The results indicate that the nursing students undergo SM at a maximum rate compared to the other two datasets.

Table 2 reports the classification results of the SVM method on the English dataset. The results imply that the SVM model reaches effectual outcomes under all classes. For instance, with >5 times, the SVM model obtains $accu_y$ of 93.27%, $prec_n$ of 92.41%, $reca_l$ of 91.66%, and $F_{score}$ of 91.00%. Similarly, whenever needed, the SVM model attains an $accu_y$ of 91.60%, $prec_n$ of 93.63%, $reca_l$ of 91.34%, and $F_{score}$ of 91.88%. Moreover, the SVM model reaches an average $accu_y$ of 93.27%, $prec_n$ of 92.41%, $reca_l$ of 91.66%, and $F_{score}$ of 91.00%.

Table 3 depicts the classification outcomes of the SVM approach on the Maths dataset. The outcomes stated that the SVM system reaches effectual outcomes under all classes. For instance, with >5 times, the SVM method obtains $accu_y$ of 95.07%, $prec_n$ of 94.62%, $reca_l$ of 93.87%, and $F_{score}$ of 94.06%. Similarly, whenever needed, the SVM algorithm reaches an $accu_y$ of 93%, $prec_n$ of 94.30%, $reca_l$ of 93.04%, and $F_{score}$ of 94.81%. Besides, the SVM technique gains an average $accu_y$ of 94.25%, $prec_n$ of 94.60%, $reca_l$ of 94.27%, and $F_{score}$ of 94.40%.

Table 4 defines the classification results of the SVM technique on the Nursing dataset. The outcomes represent that the SVM algorithm reaches effectual outcomes under all classes. For instance, with >5 times, the SVM approach gains $accu_y$ of 95.50%, $prec_n$ of 95.69%, $reca_l$ of 95.42%, and $F_{score}$ of 95.29%. In addition, whenever needed, the SVM approach reaches $accu_y$ of 95.96%, $prec_n$ of 95.50%, $reca_l$ of 95%, and $F_{score}$ of 95.49%. Additionally, the SVM algorithm reaches an average $accu_y$ of 95.48%, $prec_n$ of 95.75%, $reca_l$ of 95.36%, and $F_{score}$ of 95.43%. Figure 2 observes the SVM system's accuracy during training and validation on the testing dataset.

**Table 1. Details on datasets**

| Classes | Datasets | | |
|---|---|---|---|
| | English | Maths | Nursing |
| Never Taken | 1 | 3 | 5 |
| Once | 14 | 11 | 16 |
| Twice | 6 | 10 | 5 |
| Thrice | 5 | 4 | 1 |
| >5 Times | 13 | 9 | 10 |
| Whenever Need | 21 | 23 | 23 |
| **Total** | **60** | **60** | **60** |

**Table 2. Classifier outcomes of the SVM approach with various classes under the English dataset**

| English Dataset | | | | |
|---|---|---|---|---|
| **Class** | **Accuracy** | **Precision** | **Recall** | **F-Score** |
| Never Taken | 92.25 | 93.41 | 93.91 | 93.91 |
| Once | 91.80 | 93.76 | 92.09 | 92.05 |
| Twice | 93.42 | 92.05 | 91.19 | 91.06 |
| Thrice | 92.17 | 91.71 | 91.31 | 91.58 |
| >5 Times | 93.27 | 92.41 | 91.66 | 91.00 |
| Whenever Need | 91.60 | 93.63 | 91.34 | 91.88 |
| **Average** | **92.42** | **92.83** | **91.92** | **91.91** |

**Table 3. Classifier outcomes of the SVM approach with various classes under the Maths dataset**

| Maths Dataset | | | | |
|---|---|---|---|---|
| **Class** | **Accuracy** | **Precision** | **Recall** | **F-Score** |
| Never Taken | 94.09 | 94.63 | 95.51 | 93.63 |
| Once | 93.24 | 93.74 | 94.51 | 95.35 |
| Twice | 95.41 | 95.47 | 94.65 | 94.51 |
| Thrice | 94.71 | 94.62 | 93.87 | 94.06 |
| >5 Times | 95.07 | 94.81 | 94.02 | 94.05 |
| Whenever Need | 93.00 | 94.30 | 93.04 | 94.81 |
| **Average** | **94.25** | **94.60** | **94.27** | **94.40** |

**Table 4. Classifier outcomes of the SVM approach with various classes under the Nursing dataset**

| Nursing Dataset | | | | |
|---|---|---|---|---|
| **Class** | **Accuracy** | **Precision** | **Recall** | **F-Score** |
| Never Taken | 94.97 | 95.39 | 94.98 | 95.40 |
| Once | 95.18 | 95.92 | 95.94 | 95.17 |
| Twice | 95.37 | 95.85 | 95.54 | 95.76 |
| Thrice | 95.91 | 96.14 | 95.30 | 95.44 |
| >5 Times | 95.50 | 95.69 | 95.42 | 95.29 |
| Whenever Need | 95.96 | 95.50 | 95.00 | 95.49 |
| **Average** | **95.48** | **95.75** | **95.36** | **95.43** |

**Table 5. The comparative output of the proposed technique with other ML methods**

| Model | $Accu_y$ | $Prec_n$ | $Reca_l$ | $F_{Score}$ |
|---|---|---|---|---|
| The Proposed | 95.48 | 95.75 | 95.36 | 95.43 |
| RF | 91.11 | 91.24 | 90.43 | 90.14 |
| DT | 90.04 | 90.64 | 92.97 | 92.78 |
| Naïve Bayes | 89.62 | 92.84 | 91.39 | 91.94 |
| LR | 92.82 | 90.74 | 90.72 | 89.88 |

The figure stated that the SVM technique attains growing accuracy values over epochs. Additionally, the growing validation accuracy over training accuracy depicts that the SVM model learns effectively on the testing dataset. The loss investigation of the SVM approach during the training and validation is illustrated on the testing dataset in Figure 3.

The outcomes imply that the SVM approach attains closer training and validation loss values. It is experiential that the SVM technique learns effectually on the test dataset. Finally, Table 5 and Figure 4 briefly compare the suggested technique with other ML models. The experimental values represent that the NB model results in minor outcomes, whereas the DT model exhibits slightly improved outcomes.

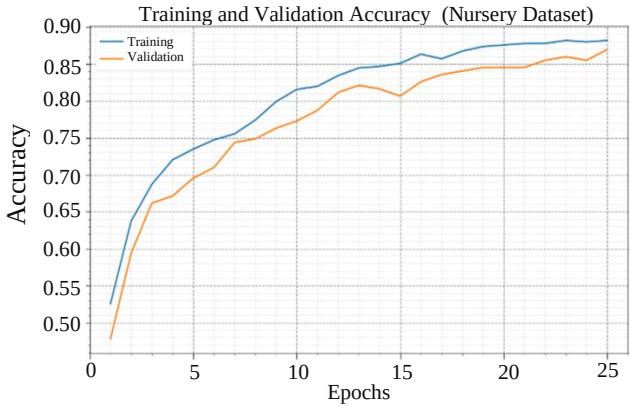


**Fig. 2 Accuracy curves of the SVM approach under the Nursing dataset**

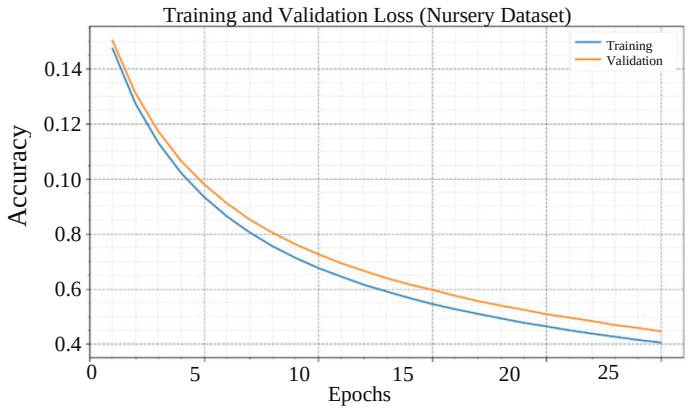


**Fig. 3 Loss curves of the SVM approach under the Nursing dataset**

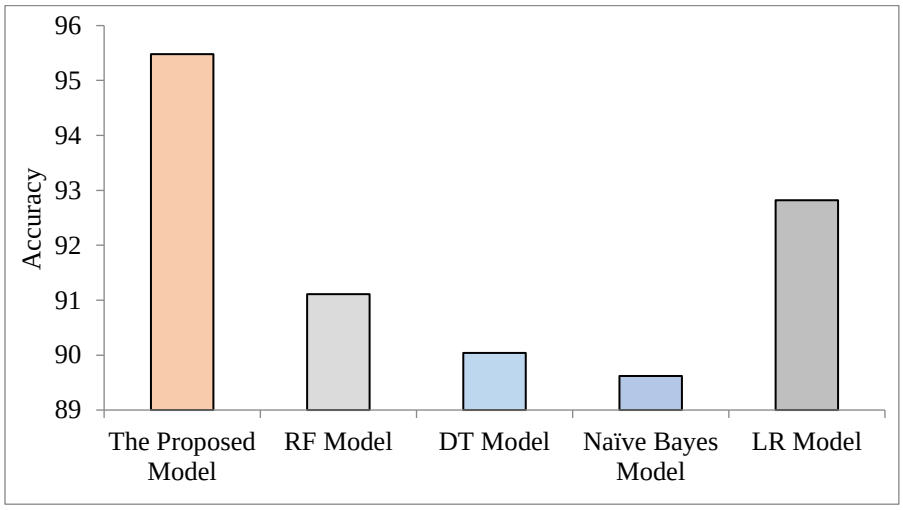


**Fig. 4 Comparative outcome of the proposed method with other ML techniques**

At the same time, the RF and LR models accomplish closer performance. But the proposed SVM model reaches better performance with a maximum accu_y of 95.48%, prec_n of 95.75%, reca_l of 95.36%, and F_score of 95.43%. These results ensured the supremacy of the SVM model.

## 5. Conclusion

Many research studies have shown that highly educated individuals have more drug use habits than less educated people. Hence, this study aims to investigate the habits relevant to drug use and the occurrence of SM practices among university students in Jazan. In this research, we have examined the pervasiveness of SM in university students globally via a comprehensive review and meta-evaluation of research published on SM among the student populace. To accomplish this, a self-administered questionnaire can be used to collect demographic variables and practice self-medication data. The data is collected amongst the undergraduate students from Aldayer university college, Jazan University, and KSA, under three disciplines: English, maths, and nursing. At the same time, the ML-based SVM model is used to predict studies undertaking high SM. The experimental results stated that nursing college studies involve more SM practices than other undergraduate students.

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## Appendix

In this study, an Institutional-based cross-sectional study design will be exploited to assess the students of University College at Aldair, JazanUniversity, KSA. The target population will be Nursing, English and math department students from all levels who meet the inclusion criteria. Five Samples from each level from all disciplines were chosen using a stratified random sample method. The five samples from each level are selected using a convenient sampling technique.

### Study Instrument

A self-administered survey will collect data on demographic variables and practice SMs.

### Demographic variables

| S. No | Variables | Details | Mark with a tick in the appropriate column |
|---|---|---|---|
| | Year of studying | First | |
| | | Second | |
| | | Third | |
| | | Fourth | |
| | Discipline | Maths | |
| | | Nursing | |
| | | English | |
| | Place of living | Jazan | |
| | | Sabya | |
| | | Aldayer | |
| | | other | |
| | History of medical illness | Yes | |
| | | No | |
| | History of SM for the past six months | Never taken SM | |
| | | Once | |
| | | Twice | |
| | | 3time | |
| | | More than five times | |
| | | Whenever need | |

### I. Knowledge questionnaire related to SMs

| S. No | Knowledge related questionnaire | Yes | No |
|---|---|---|---|
| 1 | Do you know to consume any medication needs a doctor's prescription] | | |
| 2 | Do you know the dosage of medications? | | |
| 3 | Do you read the medication leaf le before taking medications? | | |
| 4 | Do you know what is to be checked in the medication before taking it? | | |
| 5 | Do you know the adverse effect of the medication? | | |
| 6 | Do you know to manage the adverse effect of the medication? | | |
| **7** | Did you manage the side effect of medication on your own or go to the doctor? | | |

### II. What medications did you take during the past six months without a medic's prescription?

| S. No | Drugs | Mark with a tick in the appropriate column |
|---|---|---|
| 1 | Pain killers | |
| 2 | Antibiotics | |
| 3 | Drugs for fever (antipyretics) | |
| 4 | Antihistamines | |
| 5 | Cough syrups | |
| 6 | Cold and flu preparations | |
| 7 | Anti-ulcer/acidity drugs | |
| 8 | Drugs for constipation | |
| 9 | Drugs for diarrhoea | |
| 10 | Anti-emetics | |
| 11 | Nasal/Ear/Eye drops | |
| 12 | Topical agents (skin treatment agents) | |
| 13 | Nutritional/energy | |

| | | |
|---|---|---|
| | supplements/vitamins | |
| 14 | Cold and flu preparations | |
| 15 | Anti-ulcer/acidity drugs | |
| 16 | Drugs for constipation | |
| 17 | Drugs for diarrhoea | |
| 18 | Anti-emetics | |

**III. Reason for SM**

| S. No | Reason for SMs | Mark with a tick in the appropriate column |
|---|---|---|
| 1 | Body pain | |
| 2 | Tooth pain | |
| 3 | Ear problem | |
| 4 | Eye problem | |
| 5 | Fever | |
| 6 | Gastro Intestinal problem | |
| 7 | Respiratory problem | |
| 8 | Menstrual problems | |
| 9 | Insomnia | |
| 10 | Haemorrhoids | |
| 11 | Others | |

**IV. Sources of Information about the Drug**

| S. No | Sources of Information about The Drug | Mark with a tick in the appropriate column |
|---|---|---|
| 1 | Medical Students | |
| 2 | Non-Medical Students | |
| 3 | Relatives | |
| 4 | Friends | |
| 5 | Personal knowledge | |
| 6 | Mass media | |
| 7 | Past medical advice from doctors | |
| 8 | Pharmacists or those working in the pharmacy | |

**V. Where do you obtain drugs for SM?**

| S. No | A place where drugs obtained for SMs | Mark with a tick in the appropriate column |
|---|---|---|
| 1 | Pharmacy shop | |
| 2 | Online shopping | |
| 3 | Primary healthcare centre | |
| 4 | Medical representative (or) known medical professionals | |
| 5 | Friends/family | |