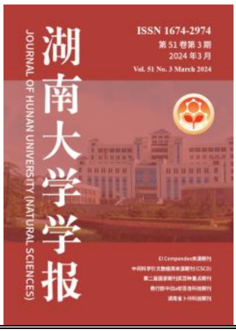

湖南大学学报（自然科学版）
Journal of Hunan University (Natural Sciences)

第 51 卷 第 3 期
2 0 2 4 年 3 月

Available online at http://jonuns.com/index.php/journal/index

Vol. 51 No. 3
March 2024

Open Access Article https://doi.org/10.55463/issn.1674-2974.51.3.3

Prediction of Sexual Violence against Women (SVAW) Using Machine Learning

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Received: December 8, 2023 / Revised: January 3, 2024 / Accepted: February 11, 2024 / Published: March 29, 2024

Abstract: Violence against women (VAW) constitutes a pressing issue that not only exacts a severe physical toll but also has significant psychological ramifications. The integration of technology with the healthcare sector, specifically the application of machine learning, presents a promising avenue for addressing these concerns. The objective of this study was to analyze potential factors contributing to the occurrence of VAW, especially sexual, and develop and assess a predictive process model. The research methodology employed in this study focuses on sexual violence against women (SVAW) and uses a quantitative approach. Data were collected from 600 married women through primary sources. The process model for predicting SVAW incorporates three algorithms: naive Bayes, random forest, and logistic regression. The most effective algorithm for predicting sexual violence against women was found to be random forest, with an accuracy of 90.00%. These findings offer valuable insights into the development of an enhanced process model for predicting SVAW. By harnessing the capabilities of machine learning techniques, we can gain a deeper understanding of this issue and ultimately contribute to the formulation of more targeted and effective prevention and intervention strategies tailored to the specific types of violence experienced by women.

Keywords: artificial intelligence, machine learning, Naive Bayes, random forest, logistic regression, violence against women, sexual violence.

使用机器学习预测针对女性的性暴力(声波焊)

摘要：针对妇女的暴力行为(VAW)是一个紧迫的问题，不仅造成严重的身体伤害，而且还会产生重大的心理影响。技术与医疗保健行业的整合，特别是机器学习的应用，为解决这些问题提供了一条有希望的途径。本研究的目的是分析导致VAW发生的潜在因素，尤其是性因素，并开发和评估预测过程模型。本研究采用的研究方法侧重于针对妇女的性暴力(声波焊)，并采用定量方法。数据通过主要来源从600名已婚妇女收集。预测声波焊的过程模型包含三种算法：朴素贝叶斯、随机森林和逻辑回归。预测针对女性的性暴力最有效的算法是随机森林，准确率为90.00%。这些发现为开发用于预测声波焊的增强过程模型提供了宝贵的见解

。通过利用机器学习技术的能力，我们可以更深入地了解这一问题，并最终有助于针对妇女遭受的特定类型的暴力制定更有针对性、更有效的预防和干预策略。

关键词：人工智能、机器学习、朴素贝叶斯、随机森林、逻辑回归、针对妇女的暴力、性暴力。

1. Introduction

VAW, especially SVAW, is a public health crisis of global proportions and is estimated to have affected one of three women worldwide, encompassing physical, emotional, or sexual violence. Shockingly, approximately one of three women globally has encountered intimate partner violence, reinforcing the disturbing notion that some believe they have the right to harm their female partners physically or sexually. Unfortunately, instances of violence against women often go unreported. The widespread prevalence of VAW and VAC has prompted a growing interest in addressing these issues from the perspectives of computer science (CS) and engineering [1]. Despite this urgency, there is a notable absence of predictive models within the realm of machine learning (ML) for classifying various types of violence. The need for quick and precise classification is paramount for effective intervention [2]. Similarly, there is a deficiency in using ML to gauge the scale of SVAW. Properly classifying the severity of domestic violence, ranging from mild to moderate, is crucial for determining the appropriate course of action [3], [4]. The lack of detailed descriptions regarding domestic violence behavior impedes efforts to categorize it into distinct types [5]. While data on domestic violence are limited, it is essential to recognize that the prevalence of SVAW is likely much higher than reported, giving rise to what is commonly referred to as the Iceberg Phenomenon. A preliminary study conducted on health services in 2022 revealed significant gaps. The identification of VAW was primarily based on community complaints, focusing solely on physical violence. There were no reports of psychological or economic violence, and interventions for domestic violence were restricted to addressing physical harm. Furthermore, the absence of an initial instrument for the identification of SVAW and the reliance on manual instruments for predicting violence underscore the need for a technological approach.

The application of artificial intelligence (AI) can effectively predict instances of SVAW with high accuracy through the use of machine learning. A study focused on predicting domestic violence in Bangladesh during the COVID-19 outbreak recommends the adoption of an ML-based model not only for Bangladesh but also for other countries and regions [2]. Considering the nature of the issue, the use of machine learning in predicting SVAW is highly suitable. AI employs machine learning to forecast the occurrences and types of VAW. A swift and precise implementation of this approach can lead to prompt and comprehensive interventions in handling SVAW. Analysis of several articles underscores that using ML is an appropriate solution for making quick and accurate predictions.

2. Literature Review

2.1. Concept of Violence against Women

VAW, especially when perpetrated by partners, is a significant public health and clinical concern and a violation of women’s human rights. This issue is deeply rooted in and perpetuates the conditions of gender inequality. Globally, one in three women experiences physical and/or sexual violence during their lifetime, predominantly at the hands of intimate partners [6]. These circumstances highlight gender inequality and discrimination against women. VAW encompasses any form of violence that leads to physical, sexual, or mental harm or suffering. This definition emphasizes that women’s experiences of violence extend beyond the physical realm, encompassing psychological, sexual, economic, and cultural dimensions. Identifying physical violence is straightforward compared with recognizing psychological violence, which is more subjective. Victims may not always be aware of psychological violence, making it crucial to focus on both the victims and perpetrators of such abuse.

Violence inflicted upon women is frequently perpetrated by husbands or intimate male partners, with physical, sexual, or psychological violence constituting the most prevalent forms of such abuse worldwide [6]. Acts of violence against women are commonly executed by their intimate partners and are categorized into various types [1], [6]–[8]: physical, sexual, economic, and psychological violence. The subsequent elucidation outlines each of them.

2.2. Concept of SVAW

Sexual violence encompasses any sexual act, attempt to engage in a sexual act, or other behavior directed toward a person's sexuality through coercion, regardless of the perpetrator's relationship to the victim or the setting in which it occurs. This includes rape, which is defined as the forcible penetration of the vulva or anus with a penis, other body part, or object, whether through physical force or coercion. Sexual violence also encompasses instances where individuals are compelled to engage in sexual activity against their will, driven by fear of consequences or coercion, or coerced into performing sexual acts that are embarrassing or degrading [6].

Sexual violence encompasses a spectrum of harmful behaviors, ranging from inappropriate touching to the act of rape. It can transpire within the confines of marriage and family life, often arising from coerced compliance with a spouse's demands or instances of incestuous abuse within familial or marital settings [7].

2.3. Machine Learning Algorithm for SVAW Prediction

AI presents versatile solutions to various health challenges, and its implementation of machine learning is particularly impactful in addressing issues such as SVAW. This discussion explores how AI can address SVAW, with a specific emphasis on using ML as a powerful prediction tool. An analysis of available information reveals that the recognition of SVAW primarily relies on community complaints. The response to domestic violence is predominantly directed at addressing physical abuse, neglecting comprehensive measures for other forms of violence. The absence of an initial instrument for identifying SVAW adds to the complexity of the challenge. Moreover, the predictions of SVAW solely depend on manually managed complaint-based inputs, lacking integration with technological advancements.

Improving the resolution of the SVAW issue requires precise and timely prediction of such incidents. This anticipation facilitates the swift and suitable implementation of subsequent intervention measures. To address this challenge, the current solution paradigm is grounded in a thorough analysis of relevant articles. This approach encourages interdisciplinary collaborations, especially in the field of women's reproductive health, aligning with the contemporary emphasis on leveraging AI. This strategic alignment has been clearly demonstrated in numerous articles [9]. Another research problem tackled through a machine learning approach pertains to the health sector, specifically involving a longitudinal study aimed at developing a prediction model for children's BMI in Malaysia, encompassing all states of the country. In addition, a systematic review was conducted to provide a comprehensive methodology for assessing and comparing classification techniques. AI has been instrumental in the detection of COVID-19 from medical images [10], [11]. Information technology has significantly impacted the realm of education, leading to changes in learning environments and styles due to technological advancements, thereby highlighting the emergence of digital disparities. This underscores the importance of integrating information technology across various domains, making computer science, especially artificial intelligence, a suitable solution for problem-solving [12], [13].

In the realm of AI, a crucial avenue involves accurately predicting SVAW using machine learning. Illustrative examples are [1], [14], [15], which focused on identifying the age groups most susceptible to violent behaviors. The study's findings were subsequently shared with law enforcement and related agencies, contributing to more informed decisions aimed at combating crimes against women in India. The analysis of articles reveals that various ML algorithms, such as random forest, logistic regression, and naive Bayes, are employed to predict SVAW. These algorithms enhance the applicability and accuracy of predicting different types of VAW, one of which is SVAW. The three most widely used algorithm models for predicting violence against women are random forest, naive Bayes, and logistic regression.

Several articles emphasize the appropriateness of using ML to predict VAW. Notably, the Random Forest algorithm demonstrated the highest accuracy rate at 92%. Random forests are renowned for their exceptional performance in tackling classification problems and do not necessitate feature scaling [16]. The discrepancy in accuracy rates could be attributed to differences in sample sizes, diverse data sources, and distinct methodologies in implementing machine learning. Despite this, refining the accuracy of VAW prediction could further optimize predictive outcomes, especially for SVAW.

3. Methodology

3.1. Research Approach

In this study, primary data were gathered from respondents using a questionnaire specifically crafted to extract variables or characteristics related to women. This research employed algorithms such as random forest, logistic regression, and naive Bayes to predict the incidence of sexual violence against women. The focus was on designing algorithms that enhance the applicability and accuracy of predicting SVAW, and the study also explores the evaluation of ML algorithms dedicated to this prediction task.

3.2. Population, Sample, and Instrument

This study focused on married women residing in Banjarmasin, South Kalimantan, Indonesia. Participants were selected from various regions within Banjarmasin, including the south, east, central, and north areas, with recruitment occurring at health service locations in these regions. Banjarmasin, also known as "the city of a thousand rivers," is situated in the province of South Kalimantan and is deeply rooted in Banjar culture.

The population includes individuals living in suburban or rural areas and in the city center, reflecting a diverse distribution of the community. This diversity in living arrangements impacts access to information concerning the prevention and intervention of SVAW, highlighting the importance of the study's location selection. The research specifically targeted women who reported being married or having an intimate partner at some point in their lives (i.e., ever married/partnered). This inclusion criterion was based on the recognition that these women were considered "at risk" for experiencing intimate partner violence [17].

The sampling process involved obtaining the population from data related to women's visits to health services. Subsequently, the researchers were stationed at predetermined health service locations, where they awaited the arrival of married women seeking health services until a specified sample size of 600 married women was met. The research employed a structured questionnaire comprising two parts. The first part gathered information on the characteristics of the respondents, while the second part focused on VAW. The latter included statements detailing symptoms or experiences of violence encountered by women. The questionnaire used in this study was developed on the basis of prior research and referenced from various articles [2]–[4].

3.3. SVAW Prediction Model Process

A model based on ML was developed to assess SVAW. To ensure a balanced dataset, it was divided into a training set (80%) and a testing set (20%) for the machine learning algorithm [2], [6]. Each ML algorithm underwent individual training and testing using the respective datasets. The modeling process was initiated from the ground up with the goal of achieving the most effective model for predicting SVAW, including the prediction of specific types of violence. A visual representation of the model architecture is presented in Fig. 1 to provide a clearer understanding of the modeling process.

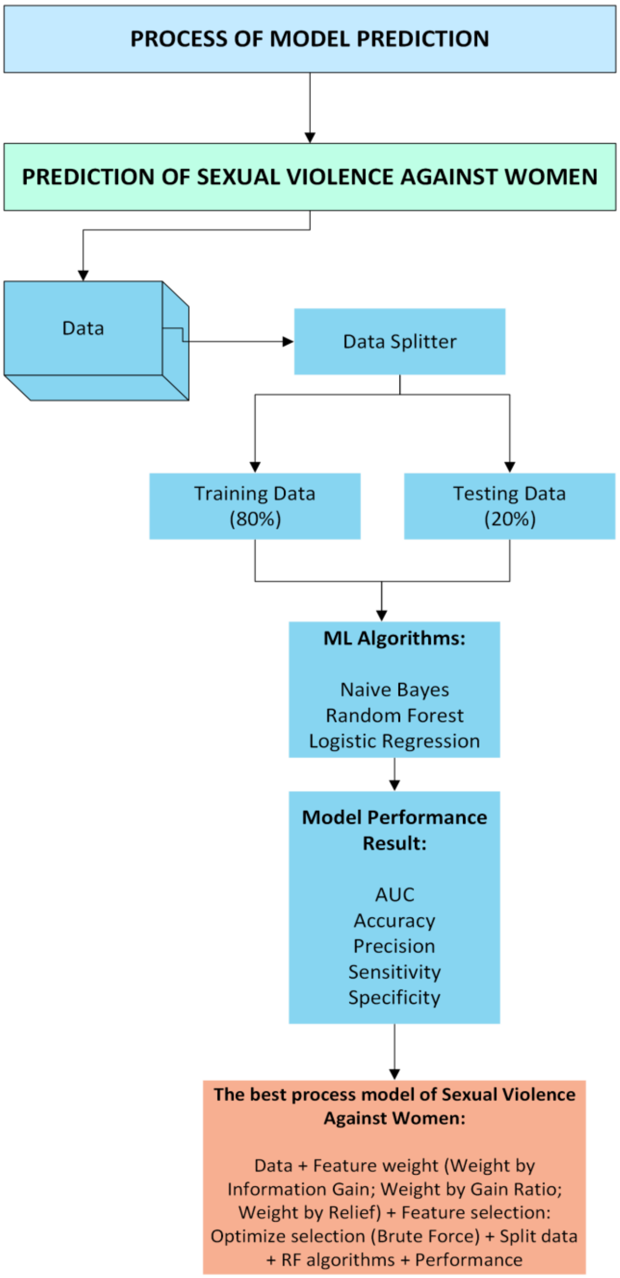

Fig. 1 SVAW framework (The authors)

The architecture comprises various components, including data collection, data splitter, and ML algorithms for model training and testing. To process the collected data, normalization and scaling techniques were employed. The processed data were then split into two groups using a data splitter. This balanced dataset is further divided into a training dataset (80%) and a testing dataset (20%) for the ML algorithm. Each ML algorithm undergoes individual training and testing using the respective datasets.

Subsequently, the performance of the model was assessed using ML algorithms such as Naïve Bayes, random forest, and logistic regression on the research dataset. This study focused on identifying the highest accuracy results to determine the most effective model for predicting SVAW. In addition to accuracy values, the model results were evaluated based on the area under the curve (AUC), precision, sensitivity, and specificity values.

4. Results and Discussion

The objective of this study was to forecast the occurrence of SVAW by analyzing the inherent risk factors among the respondents. The findings of this research start with a description of the respondent profile and the predictive model developed as part of this study.

4.1. Participants' Profile

The data provided indicates that a significant number of participants combined multiple characteristics, with the dominant outcomes as follows: 1) age: 26-35 years, occurring 179 times, accounting for 29.83% of the total; 2) marital status: married, observed in 572 cases, constituting 95.33% of the sample; 3) couple's residence: living together, reported by 584 participants, representing 97.33% of the group; 4) age at marriage: those who married before the age of 22, accounting for 51% of the respondents; 5) women education level: senior high school, with 249 individuals, amounting to 12.00%; 6) husband education level: senior high school, noted in 306 cases, corresponding to 51% of the participants; 7) gross monthly or family income: > RMW 325, representing 54.17% of the sample; 8) family types: single, reported by 561 participants, constituting 93.50% of the group; 9) number of family members: 1-4 people residing in a single house, accounting for 66.83%; 10) religion: Muslim, observed in 593 cases, amounting to 98.83%; 11) residence: rural, reported by 305 individuals, representing 50.83% of the total.

Table 1 Participants' profile based on characteristics (The authors)

Characteristics	**Specific Variable**	**Frequency**	**Percentage (%)**
Age	15–25	110	18.33
	26–35	216	36.00
	36–45	179	29.83
	46–55	73	12.17
	55 - ≥ 65	22	3.66
Marital status	Married	572	95.33
	Divorce/Widow	28	4.67
Couple's residence	LDR/Living Apart	16	2.67
	Living together	584	97.33
Age at marriage	< 22 years old	303	51
	≥ 22 years old	297	50
Women's education level	No school	1	0.17
	Primary school	70	11.67
	Junior high school	72	12.00
	Senior high school	249	41.50
	HSC (Higher Secondary Certificate)	47	7.83
	Undergraduate/Bachelor	119	19.83
	Postgraduate	41	6.83
	Ph. D.	1	0.17
Husband's education level	No school	12	2.00
	Primary school	52	8.67
	Junior high school	42	7.00
	Senior high school	306	51.00
	HSC (Higher Secondary Certificate)	32	5.33
	Undergraduate/Bachelor	128	21.33
	Postgraduate	27	4.50
	Ph. D.	1	0.17
Gross monthly income	< RMW	275	45.83
	≥ RMW	325	54.17
Women occupation	Employee	250	41.67
	Housewife	350	58.33
Husband occupation	Employee	587	97.83
	Unemployment	13	2.17
Family types	Joint	39	6.50
	Single	561	93.50
Number of family members	1–4	410	66.83
	5–8	193	32.17
	> 8	6	1.00
Religion	Muslim	593	98.83
	Christian Protestant	3	0.50
	Catholic	3	0.50
	Hindu	1	0.17
	Buddha	0	0.00
Residence	Rural	305	50.83
	Urban	295	49.17

Table 2 Participants' profile based on SVAW (The authors)

Types of VAW	Specific Variable	Frequency	Percentage (%)
Sexual Violence	Yes	153	25.50
	No	447	74.50

Derived from the frequency distribution of married women experiencing various forms of violence, the table reveals a lower prevalence of women free from violence than those who have encountered violence. Of particular concern is the issue of SVAW, with 153 women, representing 25.50%, reporting incidents. This alarming trend warrants attention from various stakeholders and will be delved into further in the subsequent discussion of this research. Multiple factors or characteristics contribute significantly to the occurrence of SVAW.

VAW often conforms to a cycle that starts with a tension-building phase arising from conflicts between couples, leading to increased tension, impaired communication, and the victim experiencing fear from their partner. The inability to assertively communicate with a partner is influenced by various factors, including the woman's level of education. Women's education is considered a pivotal step in promoting gender equality and mitigating gender-based violence. Interestingly, a gap emerged in a study, indicating that women with higher education than their husbands had a higher incidence of domestic violence. This discovery is influenced by factors such as patriarchy, culture, religion, media, and the "hidden curriculum" within the educational system [18].

This study proposes gender education as an intervention program aimed at attaining gender equality and preventing SVAW. As per the suggestions, providing women with higher education exposes them to concepts of gender equality, cultivating perspectives, insights, and skills to express their emotions and logical thoughts to their partners. This empowerment enables women to engage in effective communication, reducing the likelihood of feeling cornered or pressured during the tension-building phase and potentially impeding the progression to subsequent phases.

In-depth interviews with respondents who experienced violence further support the findings of this study. The interviews revealed that many women were reluctant to speak out, adopted a silent attitude, and struggled to convey their thoughts effectively. This lack of communication intensified the feeling of being cornered, escalated tension within the couple, and led to increased anger. Consequently, violence progressed through subsequent phases.

4.2. Predictive Model Using Machine Learning

In this study, the random forest, logistic regression, and Naive Bayes learning algorithms were employed to analyze the design of a model for predicting SVAW. The goal was to create a model that is both more applicable and accurate in predicting SVAW.

Table 3 SVAW prediction model design processes (The authors)

Types of Models	Architecture of the Model
Model 1	Data + split data + Naïve Bayes, random forest, and logistic regression
Model 2	Data + feature importance + split data + algorithm + performance
Model 3	Data + feature weight (weight by information gain, weight gain ratio, relief) + feature selection: - Forward selection - Optimize selection - Optimize selection (weight-guided) - Optimize selection (evolutionary) - Optimized selection (brute force) - Backward elimination + Split data + algorithm + performance
The best predictive model	Data + feature weight (weight by information gain, weight by gain ratio, relief) + feature selection: optimized selection (brute force) + split data + random forest + performance

Here are the outcomes of the development evaluation for each prediction model concerning SVAW, considering accuracy, precision, sensitivity, and specificity results.

From the experimental findings of crafting a prediction model for SVAW, an enhancement in the accuracy value was observed as per the constructed model. Further details are provided in Fig. 2.

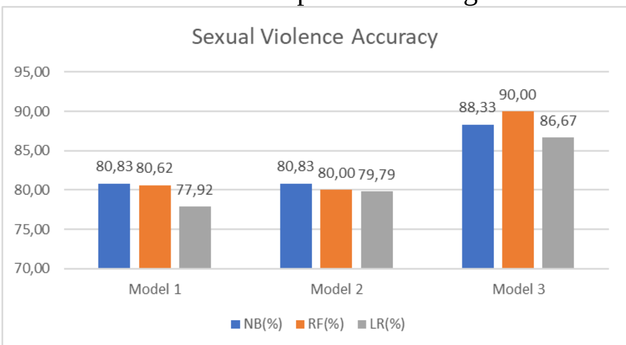

Fig. 2 Comparison of the accuracy of the prediction models for SVAW (The authors)

Table 4 Process of designing a prediction model for SVAW (The authors)

Algorithms	Accu	AUC	Pres	Sens	Spes
Model 1					
Naïve Bayes	80.83	0.700	50.00	39.13	90.72
Random Forest	80.62	0.773	51.89	27.54	93.51
Logistic Regression	77.92	0.748	47.85	21.86	91.58
Model 2					
Naïve Bayes	86.67	0.848	100	30.43	100
Random Forest	87.50	0.857	75.00	52.17	95.88
Logistic Regression	85.83	0.754	100	26.09	100
Model 3					
Naïve Bayes	88.33	0.747	80.00	52.17	96.91
Random Forest	90.00	0.909	78.95	65.22	95.88
Logistic Regression	86.67	0.851	81.82	39.13	97.94

Notes: Accu - accuracy; AUC - area under the curve; Pres - precision; Sens - sensitivity; Spes - specificity

Concerning the accuracy results in creating a predictive model for SVAW, the study indicated that the random forest model proved to be the most effective. Significant and noteworthy improvements in accuracy values were observed across all experimentally implemented models, evolving from the initial model to the third model during the prediction model creation process. Table 5 illustrates the progression of accuracy enhancements observed throughout the development of the first model to the third model.

Table 5 Increased accuracy before and after optimization of the best model (The authors)

Model 1 (Before Optimization)	Accu	Model 3 (After Optimization)	Accu	Accuracy Difference
Data set + split data + random forest	80.62	Data + feature weight + feature selection: optimized selection (brute force) + split data + random forest + performance	90.00	9.38

Drawing on the analyzed outcomes of the preceding research, several findings emerged from the process of creating a SVAW prediction model. The subsequent prediction model is derived from the analysis of the literature review results (Table 6).

Table 6 Comparison between the proposed and previous models (The authors)

References	Types of VAW	Methods	Sample	Best model and accuracy
[5]	Violence based on sexual orientation	Random Forest Variable Importance Measure (VIMs) One-R	Cyber-aggression comments	OneR: 90%
[19]	Sexual Violence on social media	Natural language processing (NLP)	Sexist comments that are publicly posted on social media (newspaper comments, social networks, etc.)	NLP: 80%
Proposed model	Sexual violence experienced by married women	Model: Split data, Feature selection, Random Forest, logistic regression, naïve bayes.	Sample: respondents focused on married women > 500 women (600)	RF: 90.00%

Based on Table 6, it becomes evident that the accuracy values obtained in this study align with those observed in previous studies. However, distinctions persist in the methodology, specifically in the choice of algorithm. While earlier research favored the One R algorithm and drew data from social media, this study employed primary data directly collected from married women and used the random forest algorithm, which yielded the highest accuracy results.

With comparing the proposed model with the previous one, several notable distinctions emerge: 1) the type of dataset utilized: Previous research relied on datasets gathered from social media, whereas this study employed direct primary data obtained from married women; 2) this research adopts a method involving data splitting, feature selection, and the use of three algorithms (random forest, naive Bayes, and logistic regression), with the random forest algorithm proving to be the most effective. In contrast, previous research identified OneR and NLP as the best algorithms.

5. Conclusion

The process of developing a predictive model for SVAW starts with data collection followed by validation using optimal training and testing data in an 80:20 ratio. Three algorithms, namely Naïve Bayes, random forests, and logistic regression, are employed. Subsequently, the model's performance was evaluated, covering accuracy, AUC, precision, sensitivity, and specificity, to determine the most effective model for predicting SVAW. This study unveils the outcomes of the predictive model design process, showcasing a significant improvement in performance. The design process encompasses three model iterations, with the random forest algorithm emerging as the most effective. The results underscore the potential of AI in predicting instances of SVAW, affirming ML as a practical solution for early diagnosis. This approach enables swift and accurate prediction of the risk of SVAW, providing valuable insights for timely intervention, especially concerning the risk factors embedded in the model developed in this study.

The anticipated outcome of this research is to serve as a preventive measure for reducing SVAW. It is hoped that the results will make a valuable contribution to the academic field, particularly in addressing the issue of SVAW. Academic contributions arising from this research involve presenting a larger sample size for data collection and offering a detailed account of sexual violence behaviors experienced firsthand by married women based on their real-life experiences. Furthermore, this research introduces a predictive model for SVAW, demonstrating optimal performance values that surpass the accuracy values found in the analyzed articles. The random forest algorithm was identified as the most effective model for predicting SVAW.

We suggest that future research endeavors incorporate additional predictive modeling techniques to enhance accuracy values and introduce features based on research findings, thereby developing a more intricate prediction model for SVAW. Factors such as the cultural context in a specific society should be considered. The outcomes of this study can serve as a foundational database that leverages an artificial intelligence approach through an expert system and decision support system (DSS) for subsequent research. The primary objectives are to streamline the diagnosis of victims of SVAW in a country at an early stage, determine appropriate initial steps for victims, and ensure the appropriate handling of violence based on its specific types. This involves the creation of an online application that can be swiftly used by victims, health services, and relevant sectors, facilitating effective, rapid, precise, and accurate responses to VAW. This collective effort contributes to the reduction of VAW incidents.

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