

Investigation of The Increase in Drug Use in Medan City Using The Support Vector Machine (SVM) Method

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ABSTRACT

Medan city is currently experiencing a troubling rise in the prevalence of drug abuse, necessitating effective strategies for detection and intervention. This research aims to improve the accuracy of identifying drug users in Medan using the Support Vector Machine (SVM) method. Data for the study were sourced from reputable institutions including the National Narcotics Agency (BNN), North Sumatra Regional Police (Polda Sumut), and the Health Office of Medan City. SVM was employed to analyze these datasets and distinguish between drug users and non-users. The study revealed that SVM achieved an impressive detection accuracy of 98.0%, a notable improvement compared to earlier approaches like Convolutional Neural Networks (CNN), which attained 83.33% accuracy. These findings highlight SVM's effectiveness as a robust tool for accurately identifying drug users. The outcomes of this study are anticipated to aid government entities in crafting targeted policies and strategies to combat drug abuse in Medan. By harnessing SVM technology, law enforcement and healthcare authorities can bolster their capabilities in swiftly and precisely detecting and responding to drug-related issues. This research contributes significantly to advancing methodologies in drug abuse detection, emphasizing SVM's pivotal role in achieving superior detection rates. In conclusion, the application of SVM in this study not only enhances detection accuracy but also underscores its potential as a reliable technology for addressing the growing challenge of drug abuse in urban settings like Medan. Future research could further refine SVM models and explore additional datasets to validate its efficacy in real-world scenarios, thereby strengthening efforts to mitigate the societal impact of drug misuse.

Keywords: Drugs; Support Vector Machine; Medan City

1. INTRODUCTION

The use of narcotics or illegal drugs has detrimental effects on individuals, families, and social environments (Afifudin Muhammad Yunus, 2020). These impacts pervade all levels of society, including the education sector from primary schools to universities (Sood, 2021). Narcotics are chemical substances that alter psychological conditions such as feelings, thoughts, emotions, and behaviors upon entering the human body through ingestion, inhalation, injection, or infusion (Hesri Mintawati, 2021). Drug abuse can lead to dependency and cause physical, mental, and social disorders (IFAHDA PRATAMA HAPSARI, SH., 2019).

A significant challenge in addressing drug cases is the limitations of interrogation and urine tests. Interrogations rely on the honesty of participants, while urine tests have restricted detection ranges and are susceptible to manipulation. This underscores the need for more objective and accurate investigative methods. The urgency of this issue highlights the importance of finding solutions that not only rely on conventional methods but also leverage advanced technologies to enhance the effectiveness of drug detection and investigation. One promising technology is the use of Support Vector Machine (SVM) methods in analyzing EEG (Electroencephalogram) data.

Previous research using Convolutional Neural Network (CNN) algorithms achieved an accuracy of only 83.33% (Garnis Ajeng Pamiela, 2021). For further development, researchers are interested in employing SVM methods, known for their ability to handle complex and nonlinear data relationships (Dakhaz Mustafa Abdullah, Abdulazeez, 2021). The software Win EEG is utilized for this study. EEG is a method of brain-computer interface (BCI) that processes brain activity data through electrical signals generated during ongoing brain activity and can be recorded (Haidar et al., 2021). SVM was chosen for its superior classification capabilities, expected to enhance accuracy in detecting drug use.

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This study utilizes data from a correctional institution in Binjai city, specifically Class 2A Correctional Institution Binjai. It aims to evaluate the correlation between crime rates and drug use, analyzing changes in the number of inmates arrested and imprisoned due to drug use. The primary focus is on developing a system to assist law enforcement in narcotics investigations. To achieve this goal, researchers will collaborate with various institutions and psychologists to gather EEG data, thereby enhancing the effectiveness of the implemented system.

2. LITERATURE REVIEW

Support Vector Machine

According to the research by (Baraa Taha Yaseen, 2023,) and (Jose Isagani B. Janairo, 2023) Support Vector Machines (SVM) have proven to be highly effective in classifying drug

users, demonstrating superior performance in various applications in drug design and discovery SVM, a popular machine learning algorithm, creates decision boundaries to accurately categorize data, even in complex multi-classification scenarios (Davuluri, 2023).

Electroencephalogram

By recording EEG signals from drug users and healthy controls, differences in brain networks and functional connectivity can be observed, aiding in the identification of drug addiction (Behzad Yousefipour, 2022). Furthermore, EEG data analysis in the frequency domain has revealed distinct changes in power spectrum bands among various types of substance abusers, indicating that analyzing specific frequency components can serve as biomarkers for detecting the type of drug used by individuals (Javad Haddadnia, 2023). Moreover, EEG signals have played a crucial role in distinguishing between healthy individuals and drug addicts, demonstrating the potential of EEG-based classification algorithms for effectively detecting drug addiction without requiring biological samples (Xiong, 2020).

Brain-Computer Interface

Brain-Computer Interface (BCI) is a crucial role in identifying drug users through various methods such as processing EEG signals, functional Near-Infrared Spectroscopy (fNIRS), and virtual reality (VR) rehabilitation systems. Research has shown that BCI can detect drug abuse based on patterns of brain activity, distinguishing between drug abusers and non-abusers (Xuelin Gu, 2022). Additionally, fNIRS devices have been used to analyze changes in brain activation in drug addicts, aiding in understanding the different effects of drugs on brain function (Yang Banghua, 2022). Overall, BCI technology offers a promising avenue for identifying drug users and developing effective rehabilitation strategies to address drug abuse issues.

3.

METHOD

Experiment Design

This research was conducted at one of the correctional facilities in North Sumatra Province, involving collaboration between Universitas Prima Indonesia, Universitas Padjadjaran Bandung, and a correctional facility in North Sumatra Province. The experiment involved 21 male participants aged 20 to 30 years. Before the experiment began, the participants were given an explanation about the equipment used.

Data Collecting

The following are the data collection steps outlined in the flowchart below:

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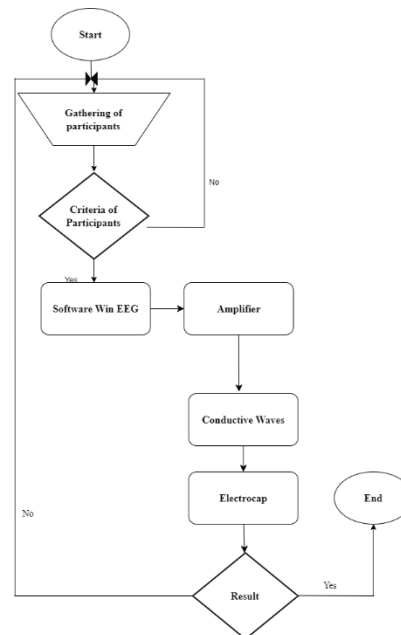


Fig. 1 Data Collecting

Participants are gathered, totaling 21 individuals, and then they are selected according to the criteria. If they do not meet the criteria, the participant selection process will be repeated. This experiment was conducted for two minutes with closed eyes. Special equipment was used to attach electrodes to the subjects' heads. The researchers conducted interviews with the subjects to gather data and information about their life histories. The success of the experiment was also influenced by the condition of the room, which needed to be quiet and free from external disturbances such as light and sound. The subjects' behavior during the experiment was carefully observed and documented. The recorded EEG data were analyzed using specialized software to understand the subjects' brain activity. In this EEG study, data from Mitsar were used to analyze brain activity. A total of 21 electrode channels were used, with 21 placed in specific areas on the scalp and 2 auricle electrodes (A1 and A2). Electrode A1 was placed on the left ear area, while A2 was placed on the right ear area. A common reference electrode was used for the electrodes placed on the auricle or ear areas.

WinEEG Software functions as the control center for the entire EEG system. This software displays the recorded EEG data in the form of brain wave graphs. Users can set recording parameters, such as sampling frequency, filters, and references.

The Amplifier is used to amplify the weak EEG signals from the brain. The amplifier boosts the EEG signals so they can be read and analyzed by the WinEEG software. It also helps reduce interference from other sources, such as noise and electrical signals.

Conductive Gel serves to conduct electrical currents between the electrodes and the scalp. Conductive gel helps reduce impedance and also enhances patient comfort during EEG recording.

Electrodes are used to detect electrical activity from the brain. The electrodes are placed at various locations on the scalp according to international standards. They capture EEG signals from the brain and send them to the amplifier.

Brain Computer Interface (BCI)

A Brain-Computer Interface (BCI) is a system that establishes direct communication between a computer and the human brain. Brain signals can be captured using Electroencephalography (EEG), which can detect various brain signals at specific frequencies. BCI can interpret a person's brain signals during motor imagery. Afterward, the signals are acquired and digitized so they can be captured by the BCI receiver. This BCI receiver can be a dongle connected to a computer.

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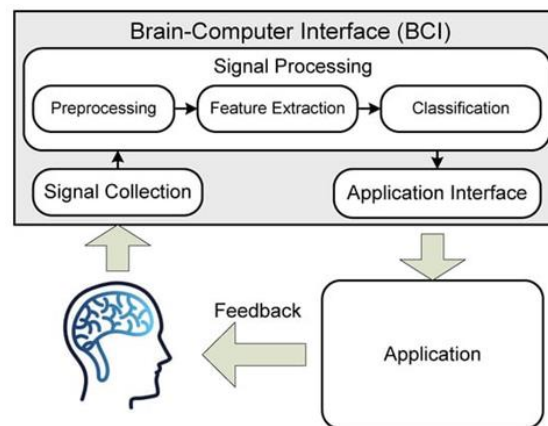


Fig. 2 BCI operation principle

Support Vector Machine

SVM is often used as an optimal margin-based classification technique that can be extended to non-linear data using kernels and various multi-class techniques (Viswanatha, 2023). Solving this optimization problem mathematically results in the SVM algorithm. There are also variations of SVM that handle non-linear data using kernel functions, which project data points into a higher-dimensional space where linear separation may be possible.

4.

RESULT AND DISCUSSION

A. Data Filtering

The data obtained is still raw with high noise levels, so it is filtered using a Band Pass Filter (BPF) with a frequency range set around 0.5 to 50 Hz. A Band Pass Filter is a specialized signal filter designed to selectively pass signals within a specific frequency range, such as alpha, beta, or other brain waves. The goal is to eliminate unwanted noise, allowing researchers or medical professionals to focus their analysis on specific brain activity. The recorded signals before and after applying the filter are depicted in Fig 3.

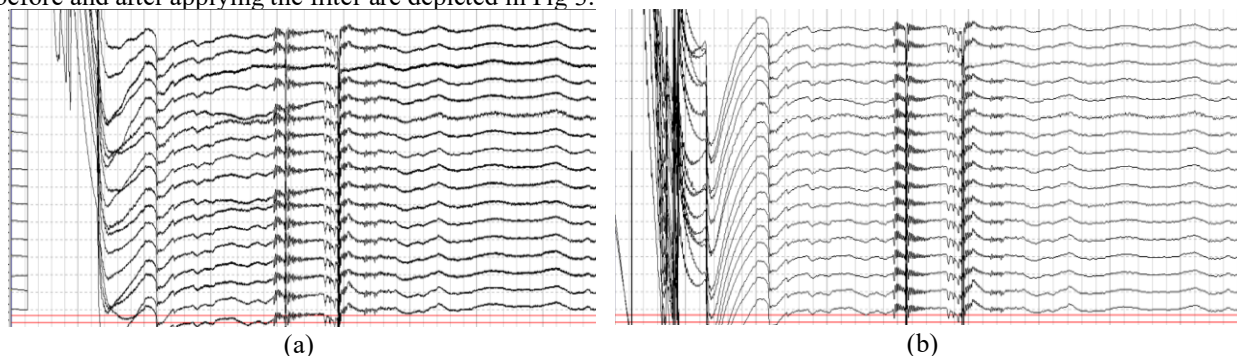


Fig. 3 (a) the signal record before and (b) after filtering

There are five brain signal waves used: delta, theta, alpha, beta 1, and beta 2. With eyes closed, theta waves become dominant when a person is in light sleep or very drowsy. Alpha waves appear when a person starts to feel relaxed or enters a resting phase. Beta waves are present when a person is engaged in full conscious mental activity, such as performing daily routines or interacting with others.

Due to the high noise level, the data needs to be filtered using a Band Pass Filter (BPF) with a frequency range of around 0.5 to 50 Hz. After that, remove Fp1 & Fp2 because we are only using 17 data points as shown in the image above, then click "OK" and wait until it's done.

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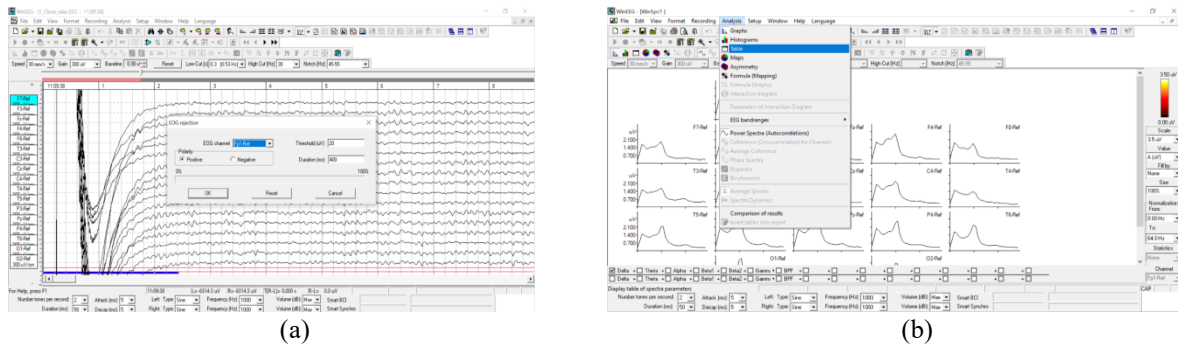


Fig. 4 BPF Filter (Band Pass Filter)

The goal is to ensure that the “Fp1 & Fp2” channels are not used because they were not utilized during data acquisition. Then, remove the EOG “Fp1 & Fp2” channels, which should look like this, and then click “OK.” Once finished, go to the analysis and click on the table, which will display the feature extraction results. The feature extraction results for each subject are shown in Table 1.

Tabel 1
Comparison of features from each subject

Subjek	Delta	Theta	Alpha	Beta1	Beta2	Gamma	Total
Fp1-Ref	10.24	9.69	24.23	1.42	1.48	0.67	47.73
F7-Ref	6	5.66	14.65	1.38	1.47	0.83	47.73
F3-Ref	7.58	11.2	32.99	1.93	1.82	0.69	29.99
Fz-Ref	8.44	11.64	33.85	1.77	1.71	0.53	56.21
F4-Ref	7.78	10.07	27.21	1.84	1.87	0.68	57.94
F8-Ref	7.22	5.5	11.58	1.33	1.57	0.97	49.45
T3-Ref	5.14	4.93	12.6	2.65	2.71	2.2	28.17
C3-Ref	6.83	8.94	28.25	1.98	1.73	0.72	30.23
Cz-Ref	9.22	11.85	38.27	2.31	2.21	0.81	48.45
C4-Ref	8.72	8.14	22.89	2.06	1.66	0.65	64.67
T4-Ref	4.84	4.06	8.58	1.24	0.94	0.51	44.12
T5-Ref	4.87	4.66	17.78	1.59	1.34	0.49	20.17
P3-Ref	8.72	8.47	30.21	2.33	1.97	0.69	30.73
Pz-Ref	7.81	8.39	31.97	2.27	1.9	0.62	52.39
P4-Ref	8.59	6.76	25.31	2.02	1.55	0.59	52.96
T6-Ref	6.19	4.01	18.84	1.48	1.24	0.56	44.82
O1-Ref	9.37	6.38	33.28	2.51	2.52	0.7	54.76
O2-Ref	6.71	4.93	26.57	2.01	1.71	0.58	42.51

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The normalized data will be classified into four categories: non-addictive, slightly addictive, potentially addictive, and highly addictive. Table 1 explains the interval for each classification category. The interval values for addiction are obtained based on Equation 1.

Tabel 2
Addictive Level

1.	Not very addictive	6,18 – 37,31
2.	Not addictive	37,31 – 68,44
3.	Potentially addictive	68,44 – 99,57
4.	Very potentially addictive	99,57 – 130,7

The "non-addictive" classification category is determined by the minimum and maximum total values, which significantly affect the interval values, with each interval having a specific range. The interval values are obtained from Equation 1 below. The calculation of the interval for each category uses the following Equation 1:

$$\text{Range} = \frac{\text{Max} - \text{Min}}{s} \quad (1)$$

Tabel 3
Formula for Support Vector Machine (SVM)

SVM	Kernel Types	Formula Definition
Linear	Linear	$K(x, y) = x, y$

SVM with Linear Kernel

$$w \cdot x + b = 0$$

Objective Function:

$$\min w, b \frac{1}{2} \|w\|^2$$

Terms:

$$\psi_i(w \cdot x_i + b) \geq 1$$

B. Confusion Matrix Graph Model

The Confusion Matrix is a table that shows the performance of a classification model in predicting data labels. For the "Potentially Addictive" class, 14.3% of the data in the first column (True Class) belongs to the "Highly Addictive" class, and 97.9% of the data belongs to the "Non-Addictive" class. In the Predicted Class, the results show that 85.7% of the "Potentially Addictive" data is correctly categorized, and 100% is categorized as "Highly Addictive." For the "Highly Addictive" data, 100% is correctly categorized, and 14.3% is correctly categorized as "Potentially Addictive".

The True Positive Rate (TPR) is the proportion of positive data correctly categorized for the "Potentially Addictive" class, with a TPR of 85.7%, and for the "Highly Addictive" class, the TPR is 97.9%. The False Negative Rate (FNR) is the proportion of positive data incorrectly categorized as negative. For the "Potentially Addictive" class, the FNR is 14.3%, and for the "Highly Addictive" class, the FNR is 100%. Both models demonstrate good performance in data classification. The results of the confusion matrix model can be seen in the following that figure:

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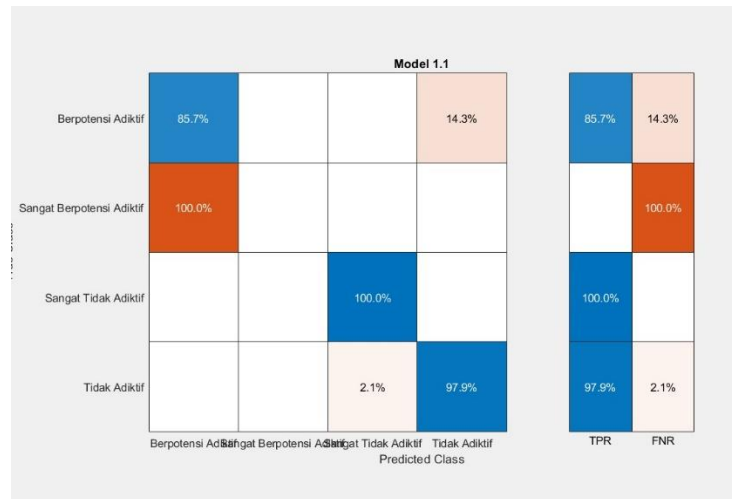


Fig. 5 Graph of Confusion Matrix

C. Scatter Plot Model

Matlab scatter plot is a graph used to visualize the relationship between two variables. In this scatter plot, each point represents one observational data. The color and shape of the points indicate different category predictions made by the model. There are various colors such as purple, green, and blue, each possibly representing different classes like "Potentially Addictive," "Classification," "Highly Addictive," "Highly Non-Addictive," and "Non-Addictive." The results of the scatter plot model can be seen in the following figure:

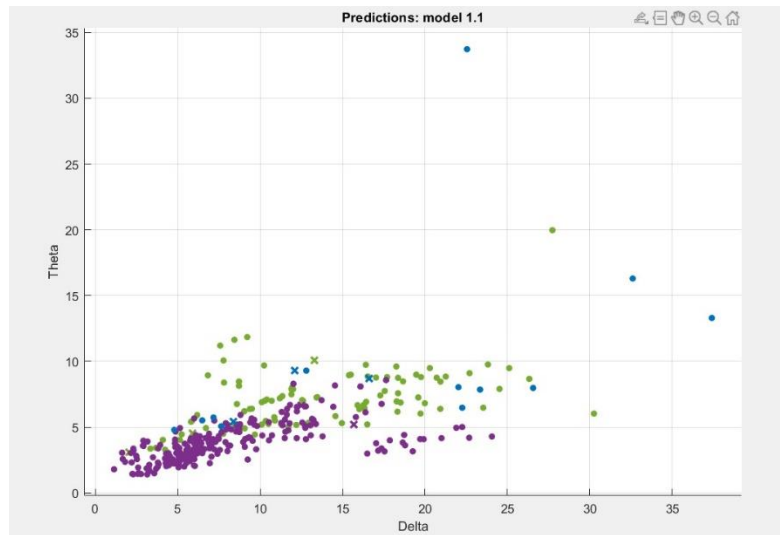


Fig. 6 Graph of Scatter Plot

D. Result of SVM Calculation

From the results of the Confusion Matrix, which is a table showing the classification model's performance in predicting data labels, and the Scatter Plot Graph, which illustrates the relationship between two variables resulting in the highest accuracy at 97.4%.

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▼ History	
1.1 ☆ SVM	Accuracy: 97.4%
Last change: Linear SVM	6/6 features
1.2 ☆ SVM	Accuracy: 96.5%
Last change: Quadratic SVM	6/6 features
1.3 ☆ SVM	Accuracy: 95.3%
Last change: Cubic SVM	6/6 features
1.4 ☆ SVM	Accuracy: 51.0%
Last change: Fine Gaussian SVM	6/6 features
1.5 ☆ SVM	Accuracy: 93.3%
Last change: Medium Gaussian SVM	6/6 features
1.6 ☆ SVM	Accuracy: 92.7%
Last change: Coarse Gaussian SVM	6/6 features

Fig. 7 Calculation result with SVM method

5. CONCLUSION

The use of drugs is increasingly prevalent across various demographics, including children. This has negative impacts on individuals, communities, and nations. This research aims to develop a drug abuse investigation system in Medan using the Support Vector Machine (SVM) method and EEG. This system is expected to enhance collaboration among correctional institutions, psychologists, and relevant parties in tackling drug abuse. Previous researchers used Convolutional Neural Networks (CNN) with 83.33% accuracy. This study proposes the Support Vector Machine (SVM) method with 98.0% accuracy, which is more effective in handling both linear and non-linear relationships. EEG is utilized to measure brain activity of drug users and aid in drug abuse case investigations. The findings of this research are expected to assist the government in providing solutions to drug abuse and safeguarding the younger generation.

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