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# MODEL ESTIMATION WITH SVM KERNEL TYPES FOR COGNITIVE DIAGNOSTICS

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**Abstract.** Support vector machine (SVM) is one of the most frequently used algorithms utilized for classification. When a classification rule is constructed through the SVM, it is of fundamental importance to evaluate its prediction accuracy. In this study, the kernel types of SVM kernels were applied on to the dataset whose attributes were based on the Wechsler Adult Intelligence Scale-Revised (WAIS-R) test, which is a test particularly designed for measuring the cognitive skills of adults on various dimensions. Dataset1 (includes all parameters of WAIS-R) and dataset2 (excluding two parameters, numbering and 3-Dimensional ability) have been analysed according to the following steps: first the SVM kernels (Linear, Quadratic, Cubic and Gaussian) were applied on dataset1 and dataset2; second computation time and accuracy rate have been calculated and compared with one to another through these four kernel types, for which 10-cross fold validation method was employed. As a result of the experiments, Gaussian kernel proved to have a higher accuracy compared to linear kernel type for both dataset1 and dataset2. The main contribution of this paper is that for the first time through the SVM kernels, the study has shown the significance of the parameters selection. The results also highlight the effect of the parameters selection both on the classification performance as well as on its significance.

**Keywords**: Support Vector Machine, model evaluation, Cognitive Diagnostics, k-fold cross-validation.

**AMS Subject Classification:** 30C40, 62G05, 62H30, 90-08, 91E10.

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## 1 Introduction

Cognitive diagnostic is a significant field of research. It is often stated that the related applications in real-world assessments have lagged behind its theoretical development due to some factors such as computational complexity and lack of model fit. Cognitive diagnosis focuses on the evaluation of a subject's strengths and weaknesses in terms of cognitive skills learned and skills that require to be worked on (Liu & Cheng, 2018). For the evaluation and classification aspect of cognitive skills, the support vector machine (SVM) comes into play. SVM is a frequently-resorted supervised learning method which aids classification decisions on attributes in a given dataset (Chiu et al., 2018).

Wechsler Adult Intelligence Scale-Revised (WAIS-R), is a clinical test made up of 11 subtests, which globally measure and demonstrate the capacity of adults concerning their voluntary movements, logical reasoning and coping (Anderson & Gerbing, 1998; Benson et al., 2010; Bentler & Bonnett, 1980). WAIS-R measures intelligence regarded as a superior mental ability which is in fact multidimensional and multi determined. WAIS-R test includes six verbal subtests as well as five performance subtests. In addition to this, it enables the calculation of verbal IQ and functional IQ at universal terms (Anderson & Gerbin, 1998; Benson et al., 2010; Bentler & Bonnet, 1980; Wechsler et al., 2008; Arceneaux et al., 1996; Daniel, 1997). Further details concerning WAIS-R can be found in references numbered (Hayslip & Panek, 1993; Kaufmanet et al., 1988; Lynn and Dai, 1993; Wechsler et al., 2008; Athanasou, 1993; Atkinson, 1991a; Atkinson, 1991b; Kaufman & Elizabeth, 2006). From the WAIS-R test we can select some parameters (for further relevant details, see e.g. (Karaca & Cattani, 2018) and references therein) which are useful for further statistical analysis. WAIS-R scale is a useful tool not only for assessing the intellectual level, but also for the opportunity to obtain information about the personality of the subject and the modalities of preferential reasoning and problem-solving.

When literature review is conducted, some recent studies have been found out with regard to the topic at hand, which aimed to relate the importance of WAIS-R test with mental disorders. First of all, studies in which different methods were used to assess cognitive aspects of humans. Lawyer and his team (Lawyer et al., 2006) set forth a model to define morphological relations regarding cognitive skills in schizophrenic cases and compute the probabilities among the relevant relations. They performed the study on 71 schizophrenic individuals and 65 individuals (as the control group) through 6 different neuropsychological tests, one of which was WAIS-R. The analysis of the link with verbal learning and working memory was conducted by Bayesian method. Neural connection of the functions of working memory, verbal learning attention, subcortical and cerebellar structures were measured. Jeffrey and his team (Arle et al., 1999) used artificial neural networks and artificial intelligence techniques for the post-operational seizure prediction of 80 epilepsy patients. ANN method was used for the predictions, which yielded a 95% of accuracy results. Sawrie and his team (Sawrie et al., 2000) used 1H magnetic resonance spectroscope to analyze the relationship between the left and right hippocampus. Statistically, Pearson correlation and neural network analysis were the methods used. In another study, Stankevicius and his team (Stankevicius, et al., 2014) worked on the positive premonitions of people about future. The measurement was conducted on 30 males and 21 females aged 17-45. There were fifty-one topics in question. For the analysis, LOT-R, Barratt NEO five factor inventory, WAIS-R number assembly and MINI international neuropsychiatric questionnaire were utilized. The result of the study showed that unrealistic optimism and the interaction of people about self-belief did not have impact on the iterative learning process.

As mentioned above, there are different methods applicable for the assessment of the cognitive aspects of humans. SVM is one of such prominent methods. One related study conducted by (Liu & Cheng, 2018) proposed the use of SVM in cognitive diagnostics. Their results show that the SVM is a method which is efficient in terms of computational aims. Therefore, this method is promising to enhance the applicability of cognitive diagnostic modeling. Another study by (Gould et al., 2014) is concerned with subtypes in schizophrenia through SVM learning approach. The results of their study indicate that the volumetric brain differences between cognitive subtypes are comparably minor in typical mixed-sex samples of schizophrenia patients, when compared with the large common disease-associated changes. The outcomes of the study also pinpoint the consideration of sex-specific differences in brain organization since this consideration has the benefit to facilitate future attempts to distinguish the patients with schizophrenia subgroups depending on the neuroanatomical features.

When compared with other works in the literature (Stankevicius et al., 2014; Gould et al., 2014; Liu & Cheng, 2018), our present study has an approach that has been employed in cognitive field along with these attributes through the use of SVM kernels (Linear, Quadratic, Cubic and Gaussian) for the first time. Wechsler Adult Intelligence Scale-Revised (WAIS-R) was administered to total of 400. The detailed explanations regarding the 21 attributes of the datasets can be found in (Karaca & Cattani, 2018). The SVM kernels have been applied in this study. This test is designed to measure and assess adults' cognitive skills on various dimensions. Two different datasets are at stake for this study. Dataset1 (600x21) includes all the parameters of WAIS-R, whereas Dataset2 (600x19) includes all the parameters in dataset1 except for two parameters, namely numbering and 3-Dimensional ability. Thus, two parameters have been excluded from Dataset2 compared to dataset1 for purposes comparison so that the significance of attributes can be emphasized. Regarding the application steps, as the first step, the SVM kernels which are Linear, Quadratic, Cubic and Gaussian were applied on the dataset1 (600x21) and Dataset2 (600x19). As the second step, computation time and accuracy rate have been calculated and compared with one another through these four kernel types, for which 10-cross fold validation method was employed.

The paper is organized as follows: Section 2 provides Materials and Methods which provide details on the dataset and SVM Kernels, respectively. Section 3 is the Experimental Results and Discussion part. And finally, Section 4 is the Conclusion part of our study.

# 2 Materials and Methods

The material under investigation includes the datasets obtained as a result of the administration of WAIS-R test on a sample of 400 healthy and 200 unhealthy individuals. SVM kernels were applied on dataset1 and dataset2.

## 2.1 Data

For our study, Wechsler Adult Intelligence Scale-Revised (WAIS-R) was administered on a total of 400 individuals, 200 of whom were healthy, and the remaining 400 were afflicted by some mental disorder. The WAIS-R dataset (600x21) was taken from the University of Massachusetts, Medical School (UMASS), Department of Neurology and Psychiatry. Problems of the patients included in the dataset are concerned with mental functioning and psychopathology (affective, mental and behavioral scopes). These parameters are provided in detail in (Karaca & Cattani, 2018).

## 2.2 Methods

The steps applied in our study are as follows:

(i) Dataset1 and dataset2 were formed based on the parameters included. Dataset1 (600x21) includes all of the WAIS-R parameters, while dataset2 (600x19) excludes two parameters, which are numbering and 3-Dimensional ability. This exclusion has been done so that the significance of the attributes could be emphasized.

(ii) We applied four SVM kernels, which are Linear, Quadratic, Cubic and Gaussian, on the dataset1 (600x21) and dataset2 (600x19).

(iii) Computation time and accuracy rate have been calculated and compared with one another through these four kernel types, for which 10-cross fold validation method was employed.

### 2.2.1 The SVM kernel types

SVM is a clustering-based classification method. It is based on the principle of not doing a more complex procedure in the preliminary stage for the solution of a simple task (Vapnik, 1998; Cortes & Vapnik, 1995). After the learning ends, the vector of the linear model's parameter is written in the subset named support vector of the learning set. These values are the ones closest to the threshold in classification. Such samples are the closest error samples close to the threshold, and they split the two thresholds. The number of the errored samples can be found by the estimation of the generalization error. The class is written as the total sum of the support vectors and the similarity between the sample data is identified by the similarity kernel function. Kernel $(G_1, G_2)$ is the criterion that measures the similarity between the two chart lines. Kernel based applications are defined as convex optimization and there is one solution that is the best. SVM is able to make very good generalizations structuring linear classification boundaries in multidimensional space through kernel (Karaca et al., 2017; Vapnik, 1998; Cortes

& Vapnik, 1995). SVM design is split by hyperplane (Karaca & Cattani, 2018) that shows the decision limits. The observations defining the boundaries are named as "support vectors". Class estimation can be performed based upon these decision limits. As regards SVM, a maximum level of accuracy is reached in the estimation of class prediction of a new set of data that is formed by using the optimum decision limit from the training data. Linear, Quadratic, Cubic, Gaussian kernel types have been used respectively in this study, and the dataset1 and dataset2 split by hyperplane of SVM algorithm has been analyzed and its accuracy rate estimation has been made.

$D$ in linear SVM, with two classes (unhealthy and healthy): training dataset and $n$ points are present in this dataset. Dataset1 is (600x21) and dataSet2 is (600x19).

$$D = \left\{ \left( (x,\ y_i) \mid x_i \in R^P,\ y_i \in \{-1, 1\} \right)_{i=1}^{n} \right\}. \tag{1}$$

The class representation of $y_i$ is $-1$ (unhealthy) or 1 (healthy). $x_i$ is a vector with $p$ dimension. $p$, is a matrix with (600x21) dimension for dataset1, and (600x19) for dataset2. The purpose is to find if the data in the input vector falls into $-1$ (unhealthy) class or 1 (healthy) by finding the appropriate hyperplane in maximum margin (Alpaydin, 2014).

$x$ in any hyperplane is denoted as follows:

$$w \cdot x - b = 0. \tag{2}$$

Since the dataset can be split linearly in this study, there are two hyperplanes as shown in Figure 1 and the representative points are support vectors. These two hyperplanes split the data and there is no data between the two hyperplanes. Afterwards, the distance between these two hyperplanes are maximized. Thus, the region borders are split into regions referred to as "margins". These hyperplanes are denoted in Equation (3) (Alpaydin, 2014).

$$w \cdot x - b = 1 \quad and \quad w \cdot x - b = -1. \tag{3}$$

The distance between these two hyperplanes are denoted as $\frac{2}{\|w\|}$ geometrically. Here the aim is to minimize the $w$ value.

$$\begin{aligned} &w \cdot x_i - b \geq 1; \quad x_i \ if \ belongs \ to \ 1.class, \\ &w \cdot x_i - b \leq -1; \quad x_i \ if \ belongs \ to \ 2.class. \end{aligned} \tag{4}$$

In this way, it is generally possible to denote $y_i(w \cdot x_i - b \geq 1);\ 1 \leq i \leq n$.

It is possible to work with different kernel types mathematically in order to identify the interclass hyperplanes while classifying the SVM data by training. The kernel function of the kernel machines on the input data is denoted as K( $x^t$, $x$). There are 25 different kernel types that could be used in SVM algorithm. ANOVA Kernel and Laplacian Kernel (Micchelli, 1986) are the counterparts of RBF kernel, Rational Quadratic Kernel is an alternative if we would like to utilize Gaussian method. Multiquadric Kernel is non-positive identified kernel and Inverse Multiquadric Kernel (Sahbi & Fleuret, 2004) is appropriate for use in infinite dimension space. Circular Kernel (Zhang et al., 2004) and Spherical Kernel are appropriate to be used for Geostatic applications. Wave kernel (Sahbi & Fleuret, 2004) is appropriate for semi defined symmetric positive data. Power Kernel (Novakovic & Veljovic, 2011) is fine for conditional positive defined applications, Spline Kernel is suitable for particular cubic polynomial data. (Basak, 2008). Log Kernel is used on images, Bessel Kernel is employed in fractional smoothness. Cauchy Kernel (Vedaldi et al., 2012) is used frequently in space with large dimension. Chi-Square Kernel (Boughorbel et al., 2005) is used merely for applications which are conditional and positive defined data. Histogram Intersection Kernel is used for image recognition, Generalized Histogram Intersection Kernel (Alashwal et al., 2009) is used for applications with large contexts. A Bayesian Kernel, Protein-protein are used in interaction data prediction. Owing to their appropriacy for being used for classification accuracy, Linear, Quadratic, Cubic and Gaussian kernel types were utilized in this study, which performed the classification between healthy and unhealthy in dataset1 and dataset2 with individuals on whom WAIS-R had been administered. For this reason, four core kernel types were opted for in our study, the details of these four kernels are provided below (see also, Karaca & Cattani, 2018):

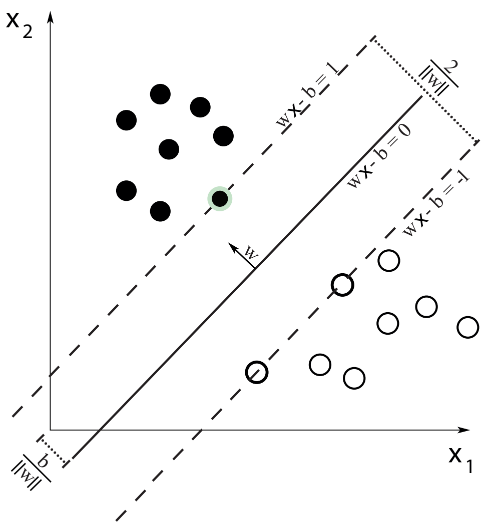



**Figure 1:** Maximum Hyperplane and Margin in SVM Training dataset1 and dataset2 with two Classes (Lu & Wang, 2014)

*Linear Kernel*

Linear Kernel is the most frequently used support vector machine kernel type.

It can conduct classifications for datasets that can be linearly split and that cannot be split linearly. The relevant equations have been formulized in (5) and (6).

$$K(x^t, x) = \langle x^t, x \rangle + c, \tag{5}$$

$$K(x^t, x) = x + c. \tag{6}$$

*Quadratic Kernel*

Quadratic Kernel, is the kernel that can split the space linearly. When the vector is converted with $\varphi(x)_i$, transition into square space is made by $\{\varphi(x)_1, \varphi(x)_2\} = \{x_1^2, x_2^2\}$. SVM distinction is made by $h\varphi(x) + b = \pm 1$ with $h = \sum c_i \varphi(x)_i$ total support vectors are found for $(x)_i$ when two equations are placed accordingly, the following denotation is provided:

$$\sum c_i K(x_i, x) + b = \pm 1. \tag{7}$$

*Cubic Kernel*

Cubic Kernel provides Equation (8), the $d$ polynomic degree described as polynomial kernel. $d$ value is 3 for cubic kernel. $x_i$, is a linear dependent vector with $d$ dimension. The classification performance result changes depending on $d$ dimension.

$$K(x_i, x_j) = \left(\gamma x_i^T x_j + r\right)^d, \gamma > 0\ . \tag{8}$$

*Gaussian Kernel*

Gaussian Kernel class prediction is made in line with Gauss distribution. This kernel is used for data that can split linearly in different space. Equation (9) provides the probability value of the weighted space between the two points

$$K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right). \tag{9}$$

# 3 Experimental Results and Discussion

Linear, Quadratic, Cubic, Gaussian are the four kernel types of SVM algorithm we applied in our study on two datasets. Data derived from the subjects were applied as input for two classes, representing the unhealthy and healthy individuals. All the parameters used in the experimental study are provided in Table 1. There are two vector sizes for the training procedure. Classification test performances were compared for four of the kernel types. Time elapsed during the training procedure was compared through these four kernels and test performance results were given based on 10-fold cross validation. Dataset details are also provided briefly in Table 1. Vectors dimension applied in the inputs are (600x21) as dataset1 and (600x19) dataset2. The results of the study were taken utilizing Matlab software.

**Table 1.** Training set explanation

| **Feature Explanation** | **Explanation** |
|---|---|
| Unhealthy | Integer number (-1) |
| Healthy | Integer number (1) |
| Participants' general Information | School education, gender, age |
| Verbal comprehension | Similarity, logical deduction, vocabulary, information, memory, comparison, QIV, QIP, QIT, VIV, VIP, VIT, DM |
| Perceptual reasoning | Finiteness or closure, numbering, assembly ability, ordering ability, 3-dimensional modeling |

Figure 2, (a) and (b) below show the steps followed during the experimental study:

Data belonging to 600 patients on whom WAIS-R test had been administered was used as SVM input data. Output with two classes (healthy and unhealthy) is in question. The performance evaluation in Linear, Quadratic, Cubic and Gaussian kernel types has been made in two aspects. The former is the time elapsed during the classification, and the latter is the test procedure based on 10-fold cross validation.

During the experimental study, complexity cost (C) value is preferred to be taken as 1 since the best value is yielded in terms of accuracy for the relevant kernel types.

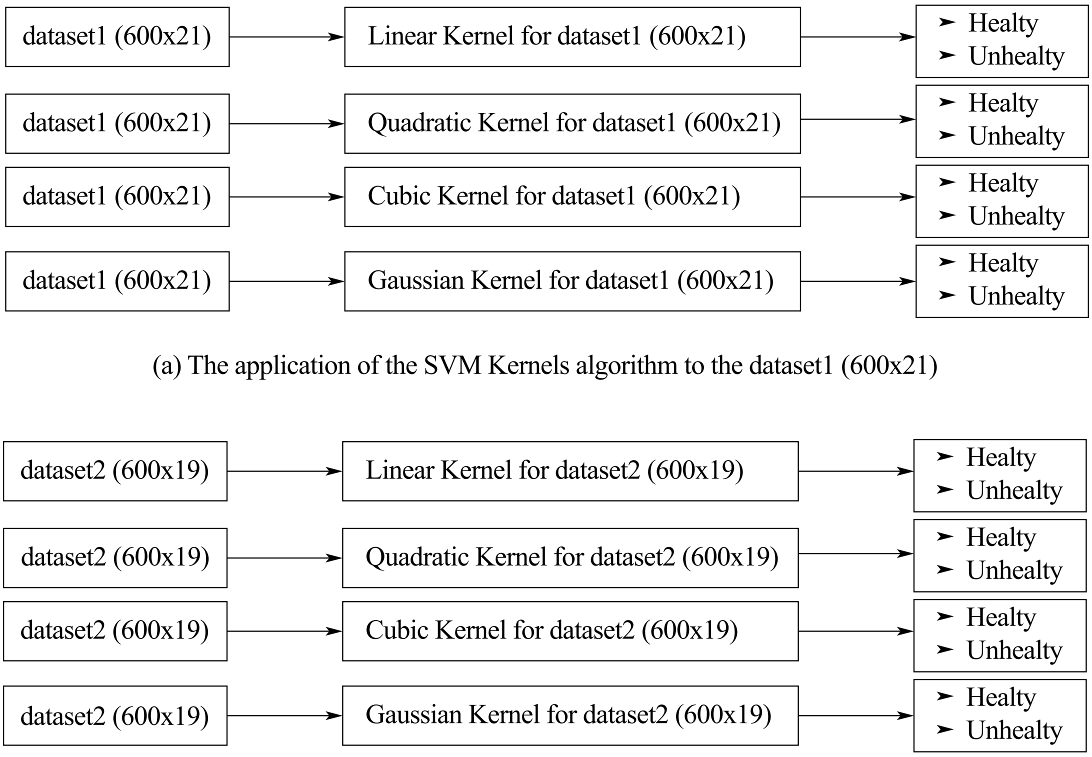
**Table 2**. Accuracy rates of classification as per healthy and unhealthy based on the Kernel Types and classification calculation time for dataset1 (600x21)

| **Kernel types** | **10- fold cross validation** | **Computation time (second)** |
|---|---|---|
| Linear kernel | 96.4 % | 12 |
| Quadratic kernel | 95.7 % | 10 |
| Cubic kernel | 94.9 % | 8 |
| Gaussian kernel | 96.4 % | 10 |

**Table 3.** Accuracy rates of classification as per healthy and unhealthy based on the kernel kypes and classification calculation time for dataSet2 (600x19)

| **Kernel types** | **10- fold cross validation** | **Computation time (second)** |
|---|---|---|
| Linear kernel | 96.4 % | 20 |
| Quadratic kernel | 95.4 % | 6 |
| Cubic kernel | 94.7 % | 8 |
| Gaussian kernel | 96.4 % | 16 |

Based on Table 2, WAIS-R analysis results belonging to 400 healthy individuals and 200 patients were used as input for the (600x21) training procedure. When the results of the experimental studies are analyzed, overall accuracy for linear kernel and Gaussian proved to be




(a) The application of the SVM Kernels algorithm to the dataset1 (600x21)

(b) The application of the SVM Kernels algorithm to the dataset2 (600x19)

**Figure 2:** Classification by four kernel types of SVM algorithm
(a) for dataset1 (600x21);
(b) for dataset2 (600x19)

96.4%, overall error are was found to be 3.6 %. For Quadratic kernel, overall accuracy was 95.7 % and overall error was 4.3 %. For Cubic kernel accuracy was 94.9 %, and the overall error was found to be 5.1 %. Based on the Kernel types, when time (in seconds) elapsed for the training and test procedure is analyzed from maximum to minimum, the order will be as follows: Linear, Quadratic, Gaussian and Cubic Kernel.

Based on Table 3, the WAIS-R analysis results belonging to 400 unhealthy individuals and 200 healthy were used as input for the training procedure. The dataset for this is (600x19) matrix with numbering and 3-Dimensional ability parameters excluded. When the results of the experimental studies are analysed, overall accuracy for linear kernel and Gaussian proved to be 96.4 %, overall error was found to be 3.6 %. For Quadratic kernel, overall accuracy was 95.4 %, and overall error was 4.6 %. For Cubic kernel overall accuracy was 94.7 %, and the overall error was found to be 5.3 %. Based on the Kernel types, when time (in seconds) elapsed for the training and test procedure is analysed from maximum to minimum, the order will be as follows: Linear, Cubic, Gaussian and Quadratic Kernel.

As a result, it has been revealed that the classification accuracy of, dataset2 is lower than that of dataset1. Class estimation of the individuals with WAIS-R test administered after removing numbering and 3-Dimensional ability parameters from dataset1 has proved to be difficult. Through the evaluation of Table 2 and Table 3, classification accuracy for Linear and Gaussian Kernel in dataset1 and dataset2 seem to be the same. However, while doing class estimation, 12 seconds is required in Linear Kernel for dataset1 whereas 20 seconds have been spent in dataset2. The class estimation accuracy of Quadratic Kernel in dataset1 is 0.03 % better than that of dataset2. As for Cubic Kernel, its class estimation accuracy in dataset1 is more than that of dataset2 by 0.02 %.

# 4 Conclusion

Support vector machine (SVM) is among the algorithms utilized for classification purposes. The major contribution we have aimed through this paper is to demonstrate the significance of the selecting the parameters for the cognitive dimensions of the individuals, for the first time in the literature, through the four SVM kernels (Linear, Cubic, Gaussian and Quadratic). When compared with other studies (Stankevicius, et al., 2014; Gould et al., 2014; Liu & Cheng, 2018), the results of this present study also highlight the significant impact of parametric selection regarding the classification performance. As for the steps applied for our approach, two datasets, dataset1 (600x21) and dataset2 (600x19), were formed. The former included all the parameters and the latter excluded two of the parameters of WAIS-R test. Such a formation of these datasets has been performed for the first time in the literature so that the significant attributes can be identified. Four SVM kernels were applied on both of the datasets. Finally, computation time and accuracy rate were computed and also compared with one another through these four kernel types, for which 10-cross fold validation method was employed. Hence, in this respect, this study aims at assisting the medical professionals and those working in related fields for the purposes of classification and accuracy so that the approach presented herein can guide them in their respective studies.

**Conflict of Interest Statement**
The authors declare no conflict of interest with regard to this paper.

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