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Elasticnet Regressive Bagging Classification for Student Academic Performance Prediction Based on Smartphone Addiction

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Abstract: Smartphones is an integral part of student lives throughout the day for communication, and entertainment, utilities, social network, and gaming. Smartphone addiction among students has a negative effect on academic performance. Different researchers carried out their research on student academic performance prediction based on Smartphone usage. But, the prediction performance was not enhanced by using conventional methods in terms of sensitivity and specificity. In order to address these existing issues, Canberra Normalized Elasticnet Regressive Bagging Classification (CNERBC) technique is introduced. The CNERBC technique comprised three steps, namely data pre-processing, feature selection and classification for performing student academic prediction. Initially, Canberra Match Data Normalization step is carried out to pre-process the data to eliminate the repeated data from the database. After that, Elasticnet Regressive Attribute Selection is carried out to select the relevant attributes of the input dataset. After selecting the relevant attributes, a classification step is performed. Ensembled Bagging Classification comprises 'N' number of C4.5 decision trees was applied for classification and prediction. In this way, an efficient student academic performance prediction is carried out in efficient manner. Experimental analysis is carried out with metrics such as accuracy, sensitivity, specificity, space complexity and time complexity. The Online system supports in education using student's academic performance (SAP) prediction using smartphones in their education system.

Keywords: *Student academic performance prediction, Smartphones addiction, Canberra match data normalization, elasticnet regressive attributes selection, Ensembled Bagging Classification*

1. Introduction

Educational data mining is a procedure employed to extract helpful information as well as patterns from huge databases, forecasting students' academic accomplishments. In the modern educational approach, the smartphone has noticeably produced in past decades of the daily lives of students, academic performance being the main area of concern. Smartphones offer numerous benefits to students' well-being and academic performance. It directly or indirectly affects a variety of issues in education.

Crucial challenges associated with smartphone usage among students are distractions in learning environments. Social media updates and other app alerts also divert students' attention from education. Excessive usage of smartphones among students has also led to health-related issues. Therefore, predicting smartphone addiction is a significant process in educational data mining to enhance student academic outcomes. Numerous Machine Learning methods were developed for smartphone addiction. However, a few essential issues were identified in obtaining exact predictions.

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The performance of middle and high-school students was forecasted [1] by stacking algorithm. However, sensitivity was not improved. A Decision tree with AdaBoost was employed [2] for Smartphone addiction prediction. But, time was not reduced. A student academic performance prediction model was introduced [3]. An applied artificial neural network (ANN) was designed [4] for calculating student academic performance. A modified Naïve Bayes classification algorithm was introduced [5] for academic performance prediction. Nevertheless, it failed to minimize space complexity.

Smartphone usage prediction was carried out [6] on mental disabilities. The relation among variables as well as the education of virtual students was explained [7]. Smartphone usage as well as sensor data was carried out [8] feature variables. Academic outcomes were combined [9]with personal characteristics as well as smartphone usage data. The academic performance of students was determined [10] to convolutional neural network (CNN).

1.1 Aim and scope of the CNERBC method

CNERBC uses Canberra Match Data Normalization for pre-processing data with minimum time as well as space complexity. Elasticnet Regressive Attribute Selection is utilized to decide appropriate attributes. Ensembled Bagging Classification is used for correct classification as well as prediction.

1.2 Novelty of the proposed CNERBC method

The main novelty of this proposed CNERBC technique is followed as,

- CNERBC Technique is introduced to perform efficient student academic performance prediction with higher accuracy based on smartphone usage.
- A novelty of Canberra Match Data Normalization Process is performed to pre-process the data for removing the repeated data from database. Every data is checked with another data to find repeated one for minimizing the dimensionality.
- An Elasticnet Regressive Attribute Selection is performed to choose the relevant attributes. After selecting relevant attributes, the classification task is carried out.
- A novelty of Ensembled Bagging Classification includes the number of C4.5 decision trees. The trained data with attributes are selected randomly for every decision tree using bootstrap random sampling. Each decision tree is grown to the maximum extent without branch deletion and votes are generated for every decision tree. The votes of all decision trees are joined to identify the majority vote of data for classification and prediction.

This research study is organized as: Segment 2, reviews the related works on student performance prediction. In Segment 3 provides concise explanation of proposed CNERBC technique. Segment 4 describes the experimental setup and performance results of the CNERBC technique. Segment 5 summarizes the key findings in the conclusion. Finally, Segment 6 provides the future work.

2. Related Work

Statistical analysis was carried out by [11] to affect student performance prediction. A new prediction algorithm was introduced [12]. Random forest algorithm was designed [13] to forecast the final exam grades with midterm exam grades. A multiclass classification model was designed [14] to forecast the final student grades. Augmented Education (AugmentED) was introduced [15] with a real-world campus dataset.

K-means clustering algorithm was introduced [16] with the discriminant analysis. A probabilistic model was introduced [17] to predict the weighted scores for face-to-face and web-based prediction. A hybrid regression model was designed [18] to enhance the prediction accuracy of student academic performance. New ensemble-based progressive prediction architecture was introduce for student performance prediction in degree programs. A visualization system was designed [19] to track and monitor student performance for helping the teachers in reorganizing the students based on performance.

Inherent ethical mechanisms and influence on academic performance was introduced [20]. However, user controls are not just a matter of default inbuilt ethical control mechanisms. Machine learning-based system with deep convoluted features was introduced [21] for the prediction of students' academic performance. Digital Addiction and Academic Students performance was introduced [22] to address this void and conducts a science mapping analysis of research addressing the relationship. Smartphone-based teacher-student interaction and teachers' helping behavior was designed [23] for teachers and students along with their relationship are addressed in the theoretical framework. FoMO was designed *[24]* for direct and positive relationship with smartphone addiction in university students. The loneliness and improve their academic performance by adopting practical strategies

3. Proposal Methodology

Our proposed system using online system supports in student academic performance is an essential factor that influences achievement of any educational institution. During education learning process, failure rates and dropouts are two essential issues faced by students. Educational Data Mining techniques provide potential impact for supporting academic institution goals to improve the quality and efficiency of learning activities and monitoring processes EDM techniques provide potential impact for supporting academic institution goals to improve the quality and efficiency of learning activities and monitoring process EDM techniques provide potential impact for supporting academic institution goals to improve the quality and efficiency of learning activities and monitoring processes

Education has crucial one in a nation growth. Educational institution provides high-quality education to students with a maximum learning process.The CNERBC technique is introduced for student academic performance prediction.

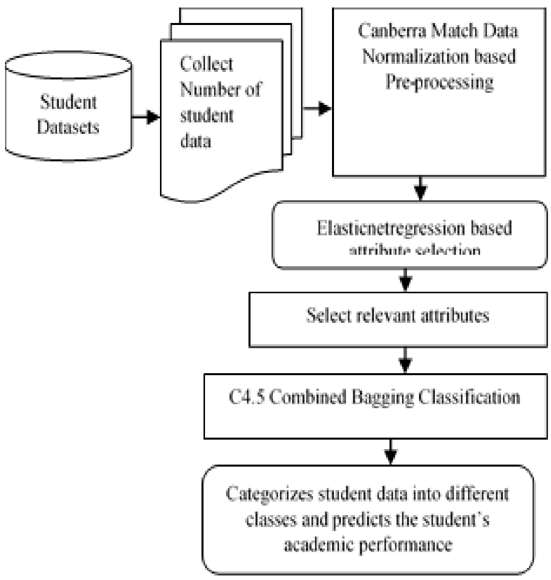

Fig 1 proposed Frame work

The flow chart of CNERBC to perform efficient student academic performance prediction based on smartphone addiction is illustrated in Figure 1. Input student data '$d_1, d_2, d_3 \ldots\ldots d_m$' collected from datasets. The collected student data with features are taken as input for Canberra Match data normalization based Pre-processing. After preprocessing, relevant attribute selection is carried out by elasticnet regression model. Student data classification is performed with higher accuracy as well as minimal time.

3.1 Dataset description

The student dataset was gathered during a survey involving 1,115 Art's and Science College students. The dataset comprises four parts namely Sociodemographic Details, Psychological Factors, Academic Performance Factors as well as Social Factors. It includes 38 attributes in the form of questions, which have been converted into numerical format. In addition, 16 smartphone addiction attributes and other relevant attributes are used. The some of the 16 smartphone addiction attributes are Purpose of smartphone usage, Mobile phone usage duration in a day, social media usage addiction both enhanced by mobile phones, and so on. Students' academic performance is classified with the aid of smartphone addiction attributes and other attributes.

3.2 Canberra Match Data Normalization based Pre-processing

First step of data pre-processing utilized in CNERBC. Data preprocessing has data mining step used to convert raw data into useful as well as efficient format. The Canberra Match Data Normalization process is to find duplicate student data during the Canberra similarity function. It is employed to recognize the linear relationship among two student performance data. It is calculated as in eq (1),

$$CS = \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{|d_i - d_j|}{|d_i| + |d_j|} \qquad (1)$$

Where, 'CS' is Canberra similarity. 'd_i' is ith student data, 'd_j' is neighboring student data. $|d_i - d_j|$ is distance among data,$|d_i|$ and$|d_j|$ is cardinality of a set which defined as the number of elements in a set in eq (1). The similarity value lies between the values '0' and '1'. Depending on this value, duplicate student data values are identified as well as removed. This helps to minimize space and time for data pre-processing.

3.3 Elasticnet Regressive Attribute Selection

The second step of attribute selection is designed in CNERBC. Elastic-net Regression has been employed for determining association among dependent as well as one or more independent variables to avoid overfitting on training data. In CNERBC, the dependent variable is the outcome of regression as well as one or more independent variables are a number of attributes in the dataset. The regression function has two outcomes such as relevant or unrelated attributes for Smartphone addiction prediction. Elastic-net regression method selects attributes based on least absolute shrinkage and selection operator (LASSO). It chooses single variable from group of highly applicable attributes as well as eliminates immaterial attributes during adding regularization terms. Elastic-net regression is described in eq (2),

$$ER = \arg\min(\|PO - \alpha A\|^2 + r_2\|\alpha\|^2 + r_1\|\alpha\|_1) \quad (2)$$

Where 'A' is attribute set '$\{A_1, A_2, A_3, \ldots . A_n\}$'. '$\|\alpha\|$' is regression term. '$r_1$' and '$r_2$' denotes the regression term with a value between '0' and '1'. 'PO' is the predicted output via regression coefficient 'ER' in eq (2). The regression coefficient returns zero for irrelevant attributes and one for relevant attributes.

3.3.1 Pseudo-code of Proposed preprocessing using Elasticnet Regressive Attribute Selection

//Table 1: Elasticnet Regressive Attribute Selection
Input: Database, Number of attributes '$A_j = A_1, A_2, A_3, \ldots \ldots . A_n$'
Output: Selected attributes
Begin **Step 1:** Number of input attributes '$A_j = A_1, A_2, A_3, \ldots \ldots . A_n$' **Step 2:For each** attribute 'A_j' **Step 3:** Compute the elasticnet regression term '$ER = \arg\min(\|PO - \alpha A\|^2 + r_2\|\alpha\|^2 + r_1\|\alpha\|_1)$ **Step 4:** $\boldsymbol{if}(0.5 > ER < 1)$ then **Step 5:** Attribute is considered as relevant attributes **Step 6:** $\boldsymbol{else}$ **Step 7:** Attribute is considered as irrelevant attributes **Step 8:**$\boldsymbol{endif}$ **Step 9**: **End for** **End**

Number of attributes is considered as input using elastic net regression is measured. Relevant features are chosen to carry out efficient student academic performance prediction.

3.4 C4.5 Combined Bagging Classification

The bagging classifier has a combination of numerous weak classifiers for efficient prediction. Each weak classifier is trained with random input student data. The bagging classifier has a Machine Learning method employed for classification to make 'n' number of C4.5 decision tree.

Assume training data i.e. mobile addiction attributes and other attributes as input of bagging classifier. Mutual information among mobile addiction attributes and other attributes and student academic performance is determined as in eq (3),

$$MI(dat_a, das_b) = \sum prob(dat_a, das_b) \log \frac{prob(dat_a, das_b)}{prob(dat_a) prob(das_b)} \quad (3)$$

Where, 'MI' is mutual information. 'dat_a' is training attribute i.e. mobile addiction attributes and other attributes, 'das_b' denote the testing attribute i.e. student academic performance in eq (3). '$prob(dat_a, das_b)$' is joint distribution probability.'$prob(dat_a)$' and '$prob(ds_b)$' is marginal probability.

$$MI(dat_a, das_b) = \begin{cases} 1, & dat_a, das_b \, are \; dependent \\ 0, & dat_a, das_b \, are \; independent \end{cases} \quad (4)$$

From eq (4), the results of mutual information '1' denotes that two data have strong relationship. Mutual information with result '0' symbolizes that two data have the weak relationship.

Then, bagging classifier combines all weak classifier into one strong classifier.

$$\sum_{i=1}^{n} WC(d_i)' = WC_1(d_i) + WC_2(d_i) + \cdots + WC_n(d_i) \quad (5)$$

Where, strong classifier results are attained in eq (5). Consequently, bagging classifierapply vote 'ϑ_i' as given in eq (6),

$$\vartheta_i \rightarrow \sum_{i=1}^{n} WC(d_i) \quad (6)$$

Consequently, bagging classifier result is computed as in eq (7),

$$BC(d_i) = arg\max_n \vartheta(WC(d_i)) \quad (7)$$

Where, '$BC(d_i)$' is final bagging classification outcome. '$arg\max_n \delta$' is majority votes of weak classifier output in eq (7). Obtained results are used for student academic performance based on smartphone addiction.

3.4.1 Pseudocode of C4.5 Combined Bagging Classification

// Table 2: C4.5 Combined Bagging Classification
Input: Student data '$d_1, d_2, d_3 \ldots\ldots d_m$ with selected Smartphone addiction attributes
Output: student academic performance prediction
Begin
Step 1: Initialize the student data $d_1, d_2, d_3 \ldots\ldots d_m$with selected attributes
Step 2:for each student data 'd_i'
Step 3: Construct weak classifiers with selected attributes
Step 4: Measure the mutual information '$MI(dat_a, das_b)$'
Step 5: If $(MI(dat_a, das_b) = 1)$ then
Step 6: Two data is mutually dependent
Step 7: else
Step 8: Two data is independent
Step 9: End if
Step 10: Combine all weak classifiers '$\sum_{i=1}^{n} WC(d_i)$'
Step 11: for each weak classifiers $WC(d_i)$
Step 12: Assign votes to every weak classifier $\vartheta_i \rightarrow \sum_{i=1}^{n} WC(d_i)$
Step 13: Find weak classifiers with majority of votes '$arg\max_n \vartheta(WC(d_i))$'
Step 14: Attain bagging classification results '$BC(d_i)$'
Step 15:end for
Step 16: end for
End

Initially, number of student data is taken as input. Bagging classifier constructs decision trees to predict student data by Smartphone addiction. It combines a decision tree and assigns votes to every decision tree result. A decision tree with higher votes is considered as final results. This method improves the classification results.

4. Results

CNERBC as well as CMN-GCCDSC implemented in Python. Training data includes summed scores of smartphone addiction as well as other features in a given preprocessed dataset. Testing data are student academic performance level namely Marginal (less than 50%), Below Average (50-60%), Average (60-70%), Above Average (70-80%), Good (80-90%), and Excellent (more than 90%). Performance is analyzed by dissimilar metrics. For experimental consideration, a number of input data are taken in a range of 200 to 1115 in steps of 200.

4.1 Results of Accuracy

It is measured as the ratio of the number of student data precisely classified to the total number of data. It is measured in percentage (%). The formula for calculating accuracy is given in eq (8).

$$Accuracy = \frac{Number\_of\_student\_data\_more\_accurately_{classified}}{Number\_of\_student\_data} * 100 \quad (8)$$

Table 3 Accuracy

Number of Student Data (Number)	Accuracy (%)	
	CMN-GCCDSC	CNERBC
200	81	85
400	83	87
600	85	88
800	87	90
1000	88	92
1115	90	94

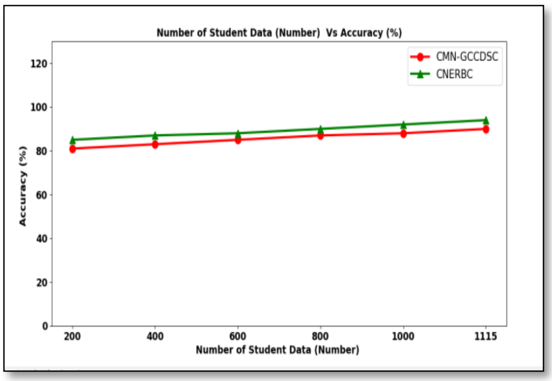

Fig. 2 Performance comparison of Accuracy using CNERBC and CMN-GCCDSC method

The results of accuracy are depicted in Figure 2. According to smartphone addiction prediction, the CNERBC technique increases the accuracy of student academic performance forecasts. The accuracy of CNERBC is improved by 4% as compared to CMN-GCCDSC.

4.2 Results of Sensitivity

It is defined as a ratio of true positives to the sum of the true positive as well as false negative from the number of student data. It is computed in percentage (%). The formula for calculating sensitivity is given in eq (9).

$$Sensitivity = \frac{True\_positive}{True\_positive+False\_Nagative} * 100 \quad (9)$$

Table 4 Sensitivity

Number of Student Data (Numbers)	Sensitivity (%)	
	CMN-GCCDSC	CNERBC
200	80	83
400	81	85
600	82	87
800	84	89
1000	85	90
1115	87	92

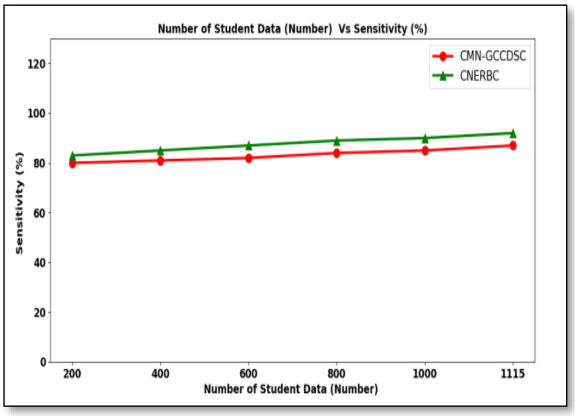

Fig. 3 Performance comparison of Sensitivity using CNERBC and CMN-GCCDSC method

Figure 3 illustrates the sensitivity for CMN-GCCDSC as well as CNERBC. The outcome of CNERBC provides superior performance. Sensitivity is enhanced by 4% by CNERBC than CMN-GCCDSC.

4.3 Results of Specificity

It has been computed as the percentage of the number of student data mistakenly classified. It is estimated in percentage (%).The formula for calculating specificity is given in eq (10).

$$Specificity = \frac{Number\_of\_student\_data\_incorrectly\_classified}{Number\_of\_studentdata} * 100 \quad (10)$$

Table 5 Specificity

Number of Student Data (Number)	Specificity (%)	
	CMN-GCCDSC	CNERBC
200	10	8
400	9	7
600	8	6
800	7	5
1000	6	4
1115	5	3

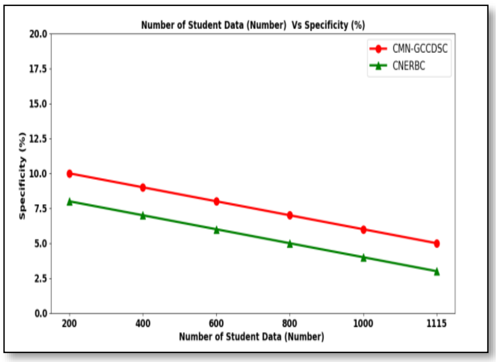

Fig. 4 Performance comparison of specificity using CNERBC and CMN-GCCDSC method

Specificity is demonstrated in Figure 4. The CNERBC technique offers better specificity than CMN-GCCDSC. The specificity of CNERBC minimized up to 41% when compared to CMN-GCCDSC.

4.4 Results of Space Complexity

It has been determined as the product of a number of student data as well as the amount of space consumed by one student's data. It is evaluated in megabytes (MB). The formula for calculating space complexity is given in eq (11).

$$SC = Number\_of\_student\_data * Space\_consumed\_by\_one\_data \quad (11)$$

Table 6 **Space complexity**

Number of Student Data (Number)	Space Complexity (MB)	
	CMN-GCCDSC	CNERBC
200	18	16
400	20	18
600	27	20
800	31	27
1000	34	30
1115	39	33

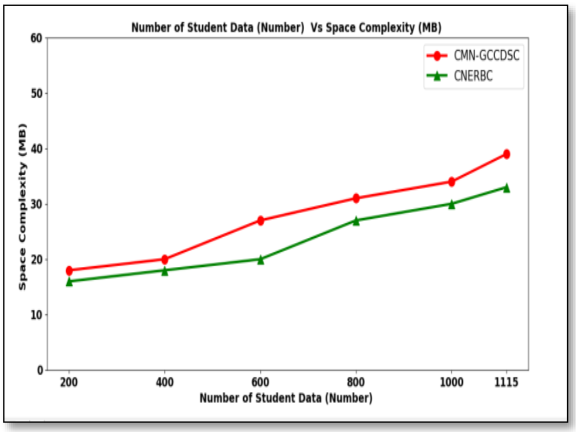

Fig 4 Performance comparison of Space complexity using CNERBC and CMN-GCCDSC method

Space complexity is explained in Figure 5. Contrary to existing CMN-GCCDSC, the CNERBC technique consumes lesser space complexity**.** The space complexity of CNERBC has been reduced by 14% than CMN-GCCDSC.

4.5 Results of Time Complexity

It is product of a number of student data and time needed by one student data. It is discovered in milliseconds (ms). The formula for calculating time complexity is given in eq (12).

$$TC = Number\_of\_student\_data * Time\_consumed\_by\_one\_data \quad (12)$$

Table 7 Time complexity

Number of Student Data (Number)	Time Complexity (ms)	
	CMN-GCCDSC	CNERBC
200	12	10
400	14	12
600	18	14
800	22	17
1000	24	21
1115	31	26

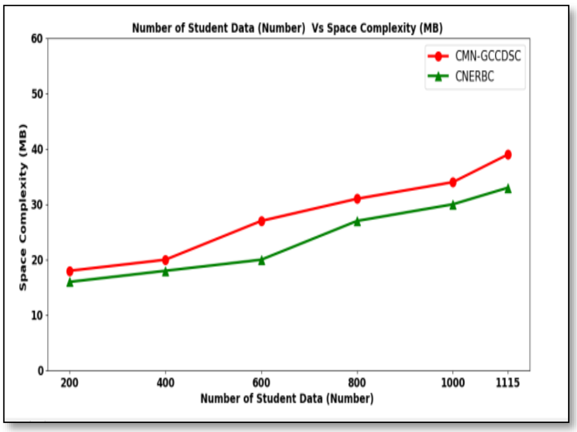

Fig 7 Performance comparison of Time complexity using CNERBC and CMN-GCCDSC method

Time complexity showed in Figure 6. Time complexity of CNERBC was reduced by 17% than CMN-GCCDSC.

5. Conclusion

A new CNERBC is introduced for performing student academic prediction based on smart phone usage. Canberra Match Data Normalization Process pre-processed the data for removing the repeated data. Following which, Elasticnet Regressive Attribute Selection is applied to the preprocessed data for selecting the relevant attributes. Finally, with the selected relevant attributes and preprocessed samples, Ensembled Bagging Classification was applied along with the decision trees for analyzing smart phone addition proneness. Each decision tree was grown to maximum extent without branch deletion. The votes were then generated for every decision tree. The votes of all the obtained decision trees were merged to identify the majority vote for data classification and prediction. By this way, student academic performance prediction based on smart phone usage is carried out in efficient manner. Elastic net regressive attribute selection chosen factor by the algorithm is compared with no of student data.

The results of CNERBC method is improved 4% of accuracy, 5%, sensitivity and minimum 40% of specificity, 14%, space complexity, and 17% of time complexity as compared to CMN-GCCDSC.

6. Future Work

Several genetic and optimization algorithm are designed to predict students academic performance with higher security. Due to presence of number of student data in smart phones, student’s academic performance prediction is a challenging one. While varying input data, data prediction cannot be distinguished effectively. It fails to predict performance level with reduced time utilization. In future, advanced feature selection method can be applied to select the relevant attributes for accurately predicting the student academic performance with minimum computational time.

6. Declaration

- **Conflict of Interest:** The author reports that there is no conflict of Interest.
- **Funding:** None
- **Acknowledgement:** None

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