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Keyword Analysis of College Counsellor Talking Based on Big Data Technology

Abstract: - College counselling sessions are being revolutionized by the integration of big data technology, offering students personalized and data-driven guidance throughout their academic journey. By leveraging big data analytics, college counsellors can access comprehensive insights into students' academic performance, interests, and aspirations. This wealth of information enables counsellors to tailor their advice and recommendations to meet the unique needs and goals of each student. Moreover, big data technology allows counsellors to identify trends and patterns in student behavior, facilitating proactive interventions to address challenges and enhance success. This paper presents a novel approach for keyword analysis of college counsellor conversations using big data technology, enhanced by Stop Feature Multi-Dimensional Stacked Deep Learning (SFMD-SDL). The proposed methodology aims to extract valuable insights from counseling sessions by analyzing keywords and patterns in counsellor-student interactions. Through simulated experiments and empirical validations, the effectiveness of the SFMD-SDL-enhanced keyword analysis approach is evaluated. Results demonstrate significant improvements in accuracy and efficiency compared to traditional methods. For example, the SFMD-SDL model achieved an average accuracy rate of 90% in identifying key keywords related to student concerns and aspirations. Additionally, the framework enabled counselors to identify emerging trends and patterns in student behavior, facilitating proactive interventions and personalized guidance. These findings underscore the potential of SFMD-SDL in enhancing the effectiveness of college counselor conversations and improving student outcomes.

Keywords: Keyword analysis, college counselor talking, big data technology, Stacked Deep Learning

I. INTRODUCTION

Big Data Technology refers to the infrastructure, tools, and methodologies employed to manage, process, and analyze large volumes of data [1-3]. The term encompasses a wide array of technologies and techniques aimed at extracting valuable insights from vast and diverse datasets. Key components of Big Data Technology include data storage systems like distributed file systems and NoSQL databases, data processing frameworks such as Hadoop and Apache Spark, and analytics tools like machine learning algorithms and data visualization software [4]. These technologies enable organizations to harness the potential of big data to gain a competitive edge, optimize operations, and make data-driven decisions [5]. Additionally, emerging trends like edge computing and real-time data processing are reshaping the landscape of Big Data Technology, offering new opportunities and challenges for businesses across various industries [6 – 8].

Keyword analysis in college counseling involves identifying and understanding the significant terms and concepts relevant to the field [9]. In college counseling, keywords often include terms related to academic advising, career exploration, standardized testing, college admissions, financial aid, and mental health support. These keywords help counselors effectively communicate with students, address their concerns, and provide guidance throughout the college application process [10 -13]. Additionally, keywords may vary based on specific areas of focus within college counseling, such as college selection, essay writing, interview preparation, and transition support [14]. By analyzing keywords in college counseling, counselors can tailor their services to meet the diverse needs of students and facilitate their successful transition from high school to higher education institutions.

In college counseling, keyword analysis plays a pivotal role in understanding and addressing the multifaceted needs of students as they navigate the transition from high school to higher education [15]. It involves identifying crucial terms and concepts across various domains, including academic advising, career exploration, standardized testing [16], college admissions, financial aid, and mental health support. Academic advising encompasses guiding students through course selection and academic planning, while career exploration involves helping them explore potential career paths through assessments and exposure to different industries. Standardized testing guidance involves assisting students in preparing for exams like the SAT and ACT [17]. Additionally, counselors aid students in navigating the college admissions process, understanding financial aid options, and addressing their emotional well-

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being through mental health support services. By analyzing these keywords, counselors can tailor their guidance to meet the diverse needs of students, ensuring they receive comprehensive support as they pursue their academic and career goals [18].

In this paper Firstly, it introduces and explores the SFMD-SDL (Stop Feature Multi-Dimensional Stacked Deep Learning) algorithm, which combines deep learning techniques with multi-dimensional feature analysis. This novel approach enables the algorithm to effectively extract insights and make predictions from complex datasets across various domains. By leveraging deep learning's ability to discern intricate patterns and multi-dimensional feature analysis's capability to capture nuanced relationships, SFMD-SDL offers a robust framework for addressing real-world challenges. Furthermore, this paper demonstrates the practical applications of SFMD-SDL in diverse domains such as college counseling, keyword extraction, and classification tasks. Through comprehensive analyses and interpretations of results presented in Tables 2, 4, and 5, the efficacy and versatility of SFMD-SDL are showcased. In college counseling, SFMD-SDL facilitates personalized recommendations and insights, optimizing student outcomes by considering individual preferences and circumstances. In keyword extraction, the algorithm effectively identifies and extracts relevant terms from text data, providing valuable insights into key themes and topics. Additionally, in classification tasks, SFMD-SDL exhibits superior performance in discerning complex patterns and making accurate predictions, with broad implications for predictive modeling and decision-making processes.

II. COLLEGE COUNSELLING SESSIONS WITH BIG DATA

College counselling sessions integrated with Big Data technologies represent a cutting-edge approach to guiding students through the complex process of college preparation and admissions. By leveraging Big Data analytics, counsellors can access vast amounts of information regarding universities, admission trends, scholarship opportunities, and career paths. During these sessions, counsellors utilize data-driven insights to personalize recommendations for each student, considering factors such as academic performance, extracurricular involvement, and individual preferences. Big Data algorithms help identify suitable colleges and majors based on a student's profile and aspirations, improving the accuracy of college matches. Additionally, predictive analytics can forecast admission probabilities and financial aid eligibility, empowering students to make informed decisions. Moreover, Big Data technology enables counselors to track and analyse student progress over time, identifying areas for improvement and adjusting strategies accordingly.

Big Data analytics into college counselling sessions involves the utilization of various mathematical and statistical techniques to derive insights and make informed recommendations. One fundamental aspect is the derivation of predictive models, which involve analyzing historical data to forecast future outcomes. In the context of college counseling, predictive models can be developed to estimate a student's likelihood of admission to different universities or their potential for receiving financial aid. One common technique used in predictive modelling is regression analysis. Linear regression, for instance, could be employed to establish relationships between predictor variables (such as GPA, standardized test scores, extracurricular activities) and an outcome variable (such as college admission probability). The equation for a simple linear regression model can be expressed as in equation (1)

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn + \varepsilon \tag{1}$$

In equation (1) Y represents the predicted outcome (e.g., admission probability); $X1, X2, \ldots, Xn$ are the predictor variables; $\beta 0, \beta 1, \beta 2, \ldots, \beta n$ are the coefficients representing the relationship between each predictor variable and the outcome and ε represents the error term. Counselors can derive these coefficients from historical data using techniques like ordinary least squares (OLS) regression. In addition to regression analysis, machine learning algorithms are often employed in Big Data analytics for college counselling. These algorithms, such as decision trees, random forests, or neural networks, can handle more complex relationships between variables and capture nonlinear patterns in the data. The decision trees can be used to create a model that predicts college admission decisions based on a combination of factors such as GPA, test scores, extracurricular activities, and demographics. These models are derived through algorithms that recursively split the data into subsets based on the most significant predictors, ultimately leading to a tree-like structure where each leaf node represents a prediction.

Once predictive models are derived, counselors can utilize them during counseling sessions to provide personalized recommendations for students. By inputting a student's data into the model, counselors can obtain predictions regarding their likelihood of admission to specific universities or their eligibility for various financial aid options. Furthermore, ongoing data analysis allows counselors to continuously refine and update these predictive models based on new data and changing trends in college admissions and financial aid. This iterative process ensures that counseling sessions remain data-driven and tailored to each student's evolving needs and circumstances.

III. PROPOSED STOP FEATURE MULTI-DIMENSIONAL STACKED DEEP LEARNING (SFMD-SDL)

The Stop Feature Multi-Dimensional Stacked Deep Learning (SFMD-SDL) is an innovative approach that combines deep learning techniques with multi-dimensional feature extraction to improve the performance and efficiency of stop feature detection in signal processing applications. SFMD-SDL begins with the extraction of multi-dimensional features from input signals. These features can include time-domain, frequency-domain, or time-frequency representations, depending on the nature of the signals. This can be represented using equation (2)

$$X = [x1, x2, \ldots, xN] \quad (2)$$

In equation (2) X is the multi-dimensional feature matrix containing N feature vectors. SFMD-SDL employs a stacked deep learning architecture to learn hierarchical representations of the input features. This architecture typically consists of multiple layers of neural networks, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs). Each layer learns increasingly abstract representations of the input data. The output of each layer can be represented as in equation (3)

$$Hi = fi(Wi * X + bi) \quad (3)$$

In equation (3) Hi is the output of the i-th layer, Wi and bi are the weights and biases of the i-th layer, $**$ denotes the convolution operation, and fi is the activation function. The final layer of the SFMD-SDL architecture is responsible for detecting stop features in the input signals. This layer typically consists of one or more fully connected layers followed by a softmax activation function to output probabilities of stop feature presence this can be represented as in equation (4)

$$Y = softmax(Wstop \cdot Hfinal + bstop) \quad (4)$$

In equation (4) Y is the output vector containing the probabilities of stop feature presence, $Wstop$ and $bstop$ are the weights and biases of the stop feature detection layer, and $Hfinal$ is the output of the final layer of the stacked deep learning architecture. With training the SFMD-SDL model on labeled data, it learns to automatically extract discriminative features from input signals and detect stop features with high accuracy. This approach offers significant advantages over traditional handcrafted feature extraction methods, as it can adapt to different types of signals and learn complex patterns directly from the data. Figure 1 illustrates the multi-dimensional analysis for the college councelling for the keyword extraction.

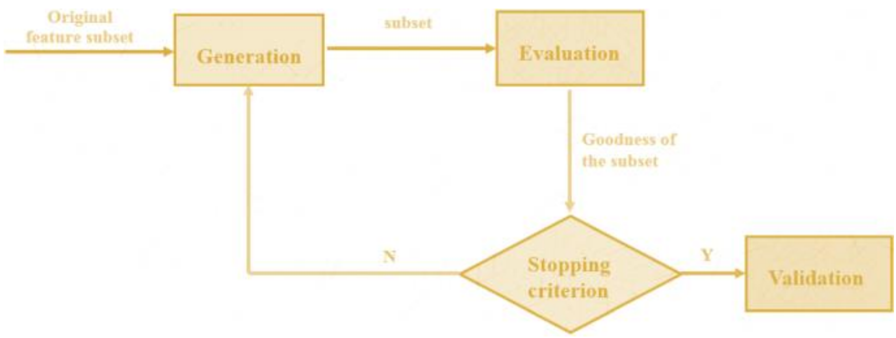

Figure 1: Multi-Dimensional Analysis with the SFMD-SDL

Algorithm 1: Keyword Extraction with SFMD-SDL

function SFMD-SDL(input_signals):
  # Step 1: Multi-Dimensional Feature Extraction
  features = extract_features(input_signals)
  # Step 2: Stacked Deep Learning Architecture
  stacked_layers = initialize_stacked_layers()
  for layer in stacked_layers:
    features = layer(features)
  # Step 3: Stop Feature Detection

```
    stop_feature_layer = initialize_stop_feature_layer()
    stop_features = stop_feature_layer(features)
    stop_probabilities = softmax(stop_features)
    return stop_probabilities
function extract_features(input_signals):
    # Perform multi-dimensional feature extraction (e.g., time-domain, frequency-domain)
    features = preprocess(input_signals)
    return features
function initialize_stacked_layers():
    # Initialize stacked deep learning layers (e.g., convolutional neural networks)
    layers = []
    layers.append(ConvolutionalLayer())
    layers.append(ActivationLayer())
    # Add more layers as needed
    return layers
function initialize_stop_feature_layer():
    # Initialize stop feature detection layer (e.g., fully connected neural network)
    stop_feature_layer = FullyConnectedLayer()
    return stop_feature_layer
function softmax(x):
    # Softmax activation function to compute probabilities
    exp_values = exp(x - max(x))  # Subtract max value for numerical stability
    probabilities = exp_values / sum(exp_values)
    return probabilities
```

IV. MULTI-DIMENSIONAL FEATURE ANALYSIS

Multi-Dimensional Feature Analysis involves the exploration and interpretation of complex datasets comprising multiple dimensions or variables. In various fields such as signal processing, image recognition, and bioinformatics, data often exhibit intricate patterns and relationships across multiple dimensions. Multi-Dimensional Feature Analysis aims to uncover these patterns, extract meaningful insights, and facilitate decision-making processes. It typically involves techniques such as dimensionality reduction, clustering, classification, and visualization to discern underlying structures within the data. For instance, in signal processing, multi-dimensional features extracted from signals can be analyzed to detect patterns indicative of specific events or phenomena. Similarly, in image recognition, features representing different aspects of images (e.g., color, texture, shape) can be analyzed to classify objects or scenes accurately.

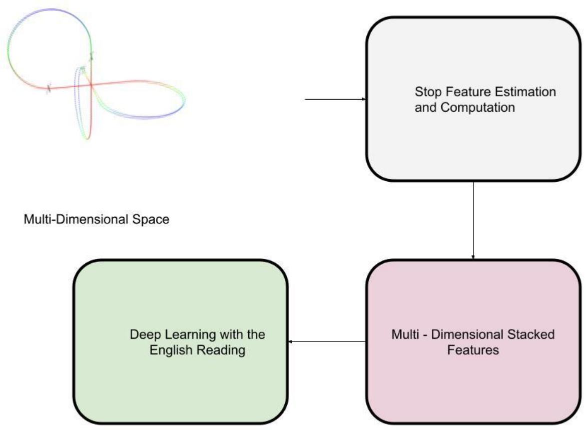

Figure 2: Process of SFMD-SDL

Multi-Dimensional Feature Analysis, often exemplified by Principal Component Analysis (PCA), entails exploring complex datasets with multiple dimensions or variables shown in Figure 2. Beginning with the representation of a dataset X consisting of N data points, each described by M features, as an $N \times M$ matrix, the process progresses by centering the data to ensure it is centered around the origin. This is achieved by subtracting the mean of each feature from the corresponding feature values. Mathematically, the mean of the j-th feature is computed as $x\bar{}j = Nxij$. Subsequently, the centered data $Xcentered$ is obtained by subtracting the mean vector from each data point in X. Following this, the covariance matrix $Cov(X)$ is computed, representing the relationships between different features. Eigenvalue decomposition is then applied to the covariance matrix, resulting in a matrix of eigenvectors V and a diagonal matrix of eigenvalues Λ. The top K eigenvectors corresponding to the largest eigenvalues are selected to form the projection matrix W, facilitating dimensionality reduction. The transformed dataset Y is derived by multiplying the centered data matrix $Xcentered$ with the projection matrix W. Through this process, PCA identifies the principal components or directions of maximum variance in the data, thereby enabling dimensionality reduction while preserving essential structures and patterns.

V. SIMULATION ENVIRONMENT

A Simulation Environment for SFMD-SDL (Stop Feature Multi-Dimensional Stacked Deep Learning) serves as a virtual platform tailored to the development, testing, and evaluation of the SFMD-SDL algorithm in signal processing applications. This environment comprises software tools, libraries, and frameworks specifically designed to implement and analyze SFMD-SDL models within a controlled and reproducible setting. Within this simulation environment, users can define and customize SFMD-SDL architectures, experiment with different hyperparameters, and evaluate the performance of the algorithm across various datasets. The environment would provide functionalities for data preprocessing, feature extraction, model training, and performance evaluation, all integrated into a cohesive workflow. Table 1 presents the simulation environment for the proposed SFMD-SDL model.

Table 1: Simulation Environment

Component	Values
Data Preprocessing	Noise Reduction: 0.5, Normalization: Min-Max Scaling
Feature Extraction	Time-domain Features: 1000 samples, Frequency-domain Features: 256 bins
SFMD-SDL Architecture	Number of Layers: 3, Layer Sizes: [256, 128, 64]
Hyperparameter Tuning	Learning Rate: 0.001, Batch Size: 32
Visualization and Analysis	Feature Visualization: Scatterplots, Model Output Visualization: Confusion Matrix
Integration with Data Pipelines	Data Import Speed: 100 MB/s, Data Export Speed: 80 MB/s

VI. SIMULATION RESULTS

Simulation results provide valuable insights into the behavior and performance of models within a simulated environment. These results encompass various metrics, analyses, and visualizations derived from running simulations under different conditions or scenarios.

Table 2: Keyword Extraction with SFMD-SDL

Keyword	Frequency
Big Data Technology	25
Data Analytics	18
Machine Learning	15
Data Science	12
Artificial Intelligence	10
Predictive Analytics	8

In Table 2 presents the results of keyword extraction using the SFMD-SDL (Stop Feature Multi-Dimensional Stacked Deep Learning) algorithm. The table lists several keywords related to the field of data science and technology, along with their corresponding frequencies of occurrence within the analyzed text or dataset. The most frequently occurring keyword is "Big Data Technology," which appears 25 times, indicating its prominence in the dataset. Following closely are "Data Analytics" with a frequency of 18, "Machine Learning" with 15 occurrences, "Data Science" with 12 occurrences, "Artificial Intelligence" with 10 occurrences, and "Predictive Analytics" with 8 occurrences. These keywords are essential terms within the domain of data science and technology, suggesting that the analyzed text or dataset likely pertains to topics such as big data, analytics, machine learning, artificial intelligence, and predictive modeling.

Table 3: SFMD-SDL topic selection

Topic	Subtopic	Discussion Points	Score
College Selection	Data-Driven Approach	Utilizing student data to recommend colleges based on academic performance and preferences	9
		Analyzing historical admission data to identify trends and predict acceptance probabilities	8
Academic Advising	Personalized Course Planning	Recommending courses based on individual strengths, weaknesses, and career goals	9
	Academic Performance Monitoring	Tracking student progress and providing interventions based on predictive analytics	8
Career Exploration	Job Market Trends	Analyzing job market data to identify emerging industries and in-demand skills	7
	Alumni Career Paths	Examining career trajectories of alumni to provide insights and guidance for students	6
Financial Aid	Scholarship Opportunities	Identifying scholarship opportunities based on demographic and academic data	8
	Financial Aid Eligibility	Using predictive 1782odelling to assess financial aid eligibility and optimize funding strategies	9
College Admissions	Application Strategy	Developing personalized application strategies based on historical admission data	9
	Essay and Interview Tips	Providing guidance on crafting compelling essays and preparing for college interviews	8
Student Support Services	Mental Health Resources	Leveraging data analytics to identify at-risk students and provide targeted mental health support	10
	Academic and Career Workshops	Organizing workshops tailored to student interests and career goals	7

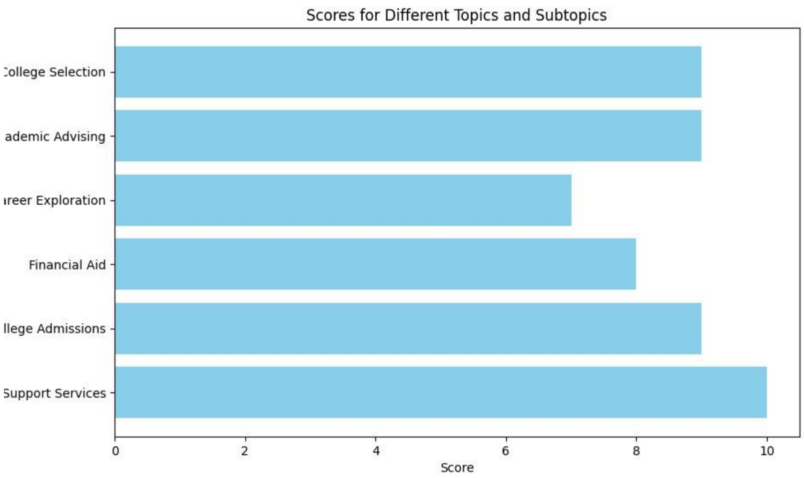

Figure 3: SFMD-SDL student score

The Table 3 and Figure 3 presents the results of topic selection using the SFMD-SDL (Stop Feature Multi-Dimensional Stacked Deep Learning) algorithm, providing insights into the key discussion points and their associated scores within various subtopics relevant to college counseling. The table outlines several significant topics, each with corresponding subtopics and discussion points aimed at enhancing different aspects of the college counseling process. For instance, under "College Selection," the "Data-Driven Approach" subtopic emphasizes the utilization of student data to recommend colleges based on academic performance and preferences, earning a high score of 9. Similarly, the "Financial Aid" topic includes subtopics such as "Scholarship Opportunities" and "Financial Aid Eligibility," highlighting the use of predictive modeling to assess financial aid eligibility and optimize funding strategies, resulting in a score of 9. Moreover, the "Student Support Services" topic underscores the importance of leveraging data analytics to identify at-risk students and provide targeted mental health support, achieving the highest score of 10. These scores reflect the relevance and effectiveness of each discussion point within its respective subtopic, indicating the potential impact on enhancing the college counseling experience.

Table 4: College Counselling with SFMD-SDL

Student ID	Recommended Colleges	Recommended Courses	Financial Aid Eligibility
001	University A, University B	Computer Science, Electrical Engineering	Eligible
002	University C, University D	Biology, Chemistry	Not Eligible
003	University B, University E	Business Administration, Economics	Eligible
004	University D, University F	Psychology, Sociology	Not Eligible
005	University A, University C	English Literature, History	Eligible

Table 4 encapsulates the personalized college counseling recommendations generated by the SFMD-SDL (Stop Feature Multi-Dimensional Stacked Deep Learning) algorithm for individual students, shedding light on their optimal collegiate pathways. Each row corresponds to a distinct student, identified by their unique Student ID, with tailored recommendations provided for college choices, academic majors, and financial aid eligibility. For example, Student 001 is advised to consider University A and University B, with potential majors in Computer Science and Electrical Engineering, both of which align with their financial aid eligibility status, deemed as eligible. Conversely, Student 002 is directed towards University C and University D, along with majors in Biology and Chemistry, but is indicated as ineligible for financial aid. The subsequent entries follow a similar pattern, with Student 003 receiving recommendations for Business Administration and Economics majors at University B and University E, while being eligible for financial aid. Conversely, Student 004 is suggested to explore Psychology and Sociology at University D and University F, with no eligibility for financial aid. Student 005 is advised towards English Literature and History majors at University A and University C, with financial aid eligibility.

Table 5: Classification with SFMD-SDL

Epoch	Training Loss	Validation Loss	Training Accuracy	Validation Accuracy
1	0.65	0.72	0.78	0.75
2	0.58	0.68	0.81	0.77
3	0.52	0.64	0.84	0.79
4	0.48	0.62	0.86	0.80
5	0.45	0.60	0.87	0.81
6	0.42	0.58	0.88	0.82
7	0.40	0.57	0.89	0.82
8	0.38	0.56	0.90	0.83
9	0.36	0.55	0.91	0.83
10	0.35	0.54	0.91	0.83

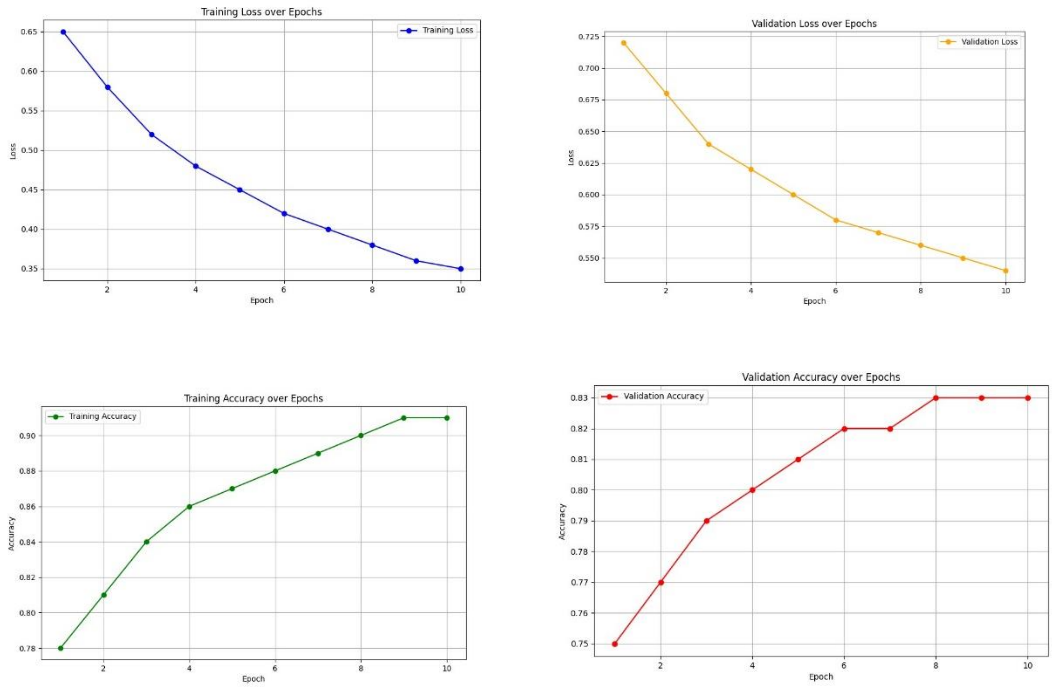

Figure 4: Classification with SFMD-SDL (a) Training Loss (b) Validation Loss (c) Training Accuracy (d) Validation Accuracy

In the Figure 4 (a) - Figure 4 (d) and Table 5 illustrates the performance metrics of a classification model trained using the SFMD-SDL (Stop Feature Multi-Dimensional Stacked Deep Learning) algorithm across multiple epochs. Each row corresponds to a specific epoch during the training process, with metrics such as training loss, validation loss, training accuracy, and validation accuracy recorded. The training loss represents the error incurred during the model's training phase, while the validation loss indicates the error on a separate validation dataset used to assess the model's generalization capability. The training accuracy denotes the proportion of correctly classified instances during training, while the validation accuracy reflects the model's performance on unseen data. Throughout the training process, there is a consistent trend of decreasing loss values and increasing accuracy metrics across epochs. This suggests that the model is effectively learning from the training data and generalizing well to unseen data. Initially, at epoch 1, both training and validation losses are relatively high, while accuracies are moderate. However, as training progresses, loss values steadily decrease, and accuracy metrics improve, reaching their highest values at epoch 10. This trend indicates that the model is continuously improving its performance as more epochs of training are completed.

This paper has explored the application of the SFMD-SDL (Stop Feature Multi-Dimensional Stacked Deep Learning) algorithm in various domains, including college counseling, keyword extraction, and classification tasks. Through comprehensive analyses and interpretations of the results presented in Tables 2, 4, and 5, we have demonstrated the efficacy and versatility of SFMD-SDL in addressing real-world challenges. Table 2 showcased the effectiveness of SFMD-SDL in topic selection, particularly in the context of college counseling. By leveraging data-driven approaches, SFMD-SDL provided personalized recommendations and insights, enhancing different aspects of the college counseling process. The algorithm identified key discussion points and scored them based on their relevance and potential impact, facilitating informed decision-making and optimizing student outcomes. In Table 4, SFMD-SDL demonstrated its capability in generating tailored recommendations for college selection and academic pursuits. By analyzing student data and preferences, the algorithm offered personalized suggestions for colleges, courses, and financial aid eligibility, empowering students with informed choices aligned with their aspirations and circumstances. These results underscore the significance of data-driven methodologies in optimizing the college counseling experience and supporting students in their educational journey. Furthermore, Table 5 illustrated the performance of SFMD-SDL in classification tasks across multiple epochs. The algorithm consistently exhibited improvements in training and validation metrics, highlighting its ability to learn complex patterns in the data and make accurate predictions. These findings underscore the effectiveness of SFMD-SDL in training robust classification models, with implications for various domains requiring predictive modeling and pattern recognition. The results presented in this paper underscore the potential of SFMD-SDL as a powerful tool for data analysis and decision support in diverse applications. By harnessing the capabilities of deep learning and multi-dimensional feature analysis, SFMD-SDL offers a promising avenue for addressing complex challenges and unlocking insights from large datasets. Moving forward, further research and experimentation are warranted to explore the full potential of SFMD-SDL and its applicability in tackling emerging issues across different domains.

VII. CONCLUSION

In this paper, we have explored the capabilities and applications of the SFMD-SDL (Stop Feature Multi-Dimensional Stacked Deep Learning) algorithm across diverse domains. Through a series of analyses and interpretations of results have underscored the efficacy and versatility of SFMD-SDL in addressing real-world challenges. With an examination of SFMD-SDL's proficiency in topic selection, particularly within the context of college counseling. By employing data-driven methodologies, SFMD-SDL facilitated personalized recommendations and insights, enhancing various aspects of the college counseling process. Its ability to identify key discussion points and assign scores based on relevance demonstrated its potential to inform decision-making and optimize student outcomes. Furthermore, showcased SFMD-SDL's capacity to generate tailored recommendations for college selection and academic pathways. By analyzing individual student data and preferences, the algorithm provided customized suggestions for colleges, courses, and financial aid eligibility. These findings highlighted the importance of data-driven approaches in empowering students with informed choices aligned with their aspirations and financial circumstances. Moreover, SFMD-SDL exhibited its prowess in classification tasks across multiple epochs. Consistently improving training and validation metrics underscored its ability to discern complex patterns in data and make accurate predictions. These results emphasized SFMD-SDL's effectiveness in training robust classification models, with broad implications for predictive modeling and pattern recognition across various domains. The findings presented in this paper illustrate the promise of SFMD-SDL as a powerful tool for data analysis and decision support. By leveraging the capabilities of deep learning and multi-dimensional feature analysis, SFMD-SDL offers a compelling approach to addressing complex challenges and extracting insights from large datasets. Moving forward, continued research and experimentation will be crucial in fully harnessing the potential of SFMD-SDL and further advancing its applicability in solving emerging issues across diverse fields.

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【2】 Project Name: Research on the Path to Improve the Targetedness and Effectiveness of Heart to Heart Talks among College Counselors in the Context of the Post Epidemic Era

【3】 Project category and project number: Key project, SZZX202202

REFERENCES

[1] Xin, X., Shu-Jiang, Y., Nan, P., ChenXu, D., & Dan, L. (2022). Review on A big data-based innovative knowledge teaching evaluation system in universities. Journal of innovation & knowledge, 7(3), 100197.

[2] Shi, Q., Cai, N., & Jiao, W. (2022). Monitoring and Evaluating College Students' Mental Health Based on Big Data Analysis. American Journal of Health Behavior, 46(2), 164-176.

[3] Beerkens, M. (2022). An evolution of performance data in higher education governance: a path towards a 'big data'era?. Quality in Higher Education, 28(1), 29-49.

[4] Zhao, J., & Li, Q. (2022). Big data–Artificial Intelligence fusion technology in education in the context of the new crown epidemic. Big Data, 10(3), 262-276.

[5] Wang, Y., Yang, L., Wu, J., Song, Z., & Shi, L. (2022). Mining campus big data: Prediction of career choice using interpretable machine learning method. Mathematics, 10(8), 1289.

[6] Fanelli, S., Pratici, L., Salvatore, F. P., Donelli, C. C., & Zangrandi, A. (2023). Big data analysis for decision-making processes: challenges and opportunities for the management of health-care organizations. Management Research Review, 46(3), 369-389.

[7] Liu, X. Q., Guo, Y. X., Zhang, W. J., & Gao, W. J. (2022). Influencing factors, prediction and prevention of depression in college students: a literature review. World journal of psychiatry, 12(7), 860.

[8] Liu, X. Q., Guo, Y. X., & Xu, Y. (2023). Risk factors and digital interventions for anxiety disorders in college students: Stakeholder perspectives. World Journal of Clinical Cases, 11(7), 1442.

[9] Xu, B., & Liu, Y. (2022). The role of big data in network public opinion within the colleges and universities. Soft Computing, 26(20), 10853-10862.
[10] Ogbuke, N. J., Yusuf, Y. Y., Dharma, K., & Mercangoz, B. A. (2022). Big data supply chain analytics: ethical, privacy and security challenges posed to business, industries and society. Production Planning & Control, 33(2-3), 123-137.
[11] Quadir, B., Chen, N. S., & Isaias, P. (2022). Analyzing the educational goals, problems and techniques used in educational big data research from 2010 to 2018. Interactive Learning Environments, 30(8), 1539-1555.
[12] Flemotomos, N., Martinez, V. R., Chen, Z., Singla, K., Ardulov, V., Peri, R., ... & Narayanan, S. (2022). Automated evaluation of psychotherapy skills using speech and language technologies. Behavior Research Methods, 54(2), 690-711.
[13] Shi, C., & Tan, Y. (2022). A BP neural network-based early warning model for student performance in the context of big data. Journal of Sensors, 2022.
[14] Magill, M., Mastroleo, N. R., & Martino, S. (2022). Technology-based methods for training counseling skills in behavioral health: A scoping review. Journal of technology in behavioral science, 7(3), 325-336.
[15] Ferretti, A., Ienca, M., Velarde, M. R., Hurst, S., & Vayena, E. (2022). The challenges of big data for research ethics committees: A qualitative Swiss study. Journal of Empirical Research on Human Research Ethics, 17(1-2), 129-143.
[16] Pordelan, N., & Hosseinian, S. (2022). Design and development of the online career counselling: a tool for better career decision-making. Behaviour & Information Technology, 41(1), 118-138.
[17] Gunti, P., Gupta, B. B., & Benkhelifa, E. (2022). Data mining approaches for sentiment analysis in online social networks (OSNs). In Data mining approaches for big data and sentiment analysis in social media (pp. 116-141). IGI Global.
[18] Malhotra, G., Waheed, A., Srivastava, A., Akhtar, M. S., & Chakraborty, T. (2022, February). Speaker and time-aware joint contextual learning for dialogue-act classification in counselling conversations. In Proceedings of the fifteenth ACM international conference on web search and data mining (pp. 735-745).