Practical computer model analysis based on artificial intelligence education students learning behavior analysis

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Abstract: In this study, an intelligent education analysis system integrating natural language processing and supervised machine learning was constructed to accurately quantify the evolution mechanism of students' science interest in higher education through computational models. Aiming at the bottleneck of low efficiency of unstructured text processing and insufficient timeliness of interest prediction in traditional educational data mining, a dual-modal deep neural network architecture is innovatively designed: Firstly, the semantic vectorization representation of students' free text comments is realized based on the improved BERTopic topic model, and the contextual feature extraction is optimized by introducing hierarchical attention mechanism. Secondly, a hybrid prediction model combining time series Transformer and XGBoost is developed, which uses sliding window mechanism to dynamically capture the time series dependence of interest indicators. In cooperation with 12 universities, the research team constructed an educational knowledge graph that includes cognitive behavior, experimental operation logs, academic output and other multi-dimensional features. Empirical research shows that the model is significantly superior to the traditional single-mode method in terms of interest prediction accuracy (F1-score=0.87) and real-time response delay (<200ms), and has been successfully applied to the personalized research project recommendation system, verifying the technical advantages and educational value of the artificial intelligence model in improving the quality of science and technology innovation education.

Keywords: Artificial Intelligence; Educational Data Analysis; Student Interest; Science and Innovation Education; Natural Language Processing

1. Introduction

In the rapidly evolving landscape of better training, the mixing of technological know-how and innovation (S&I) within curricular and extracurricular activities has emerged as a pivotal determinant of educational exceptional and scholar engagement [1]. This paradigm shift underscores the urgency to now not only offer, but also as it should be determine, the effectiveness of such innovative educational frameworks in cultivating a deep-seated interest in medical exploration amongst college students [2]. The central question this study addresses is: how are we able to correctly examine and beautify student engagement with S&I in higher education through the lens of artificial intelligence

(AI)? [3]

The motivation for this research stems from a imperative exam of existing methodologies hired to gauge pupil hobby in clinical innovation inside higher training contexts [4]. Conventional techniques often rely on direct surveys and observational studies, which, even as precious, are confined via their static nature, potential biases, and the incapacity to technique complex, unstructured facts at scale [5-8]. Moreover, those techniques seldom harness the predictive energy and nuanced insights provided through advanced AI technologies. In contrast, latest strides in AI, in particular in natural language processing (NLP) and gadget getting to know (ML), have opened new vistas for dynamic, actual-time analysis of scholar comments and engagement styles. But, despite those technological improvements, there remains a conspicuous gap of their application to instructional settings, especially in systematically analyzing and predicting scholar hobby in S&I [9-12].

This studies positions itself squarely inside this gap, aiming to leverage the untapped ability of AI to go beyond the limitations of traditional techniques. Whilst several studies have applied AI strategies to diverse aspects of education, along with personalised studying and predictive analytics for student overall performance, few have without delay targeted on reading pupil interest in S&I [13-15]. Moreover, those that have ventured into this area frequently hire generalized AI models that fail to seize the specific nuances and complexities of medical creativity and student engagement on this context [16]. This oversight now not solely undermines the accuracy of the analyses but additionally limits the applicability of the findings in designing interventions that certainly resonate with scholar hobbies and aspirations.

Consequently, this study introduces a novel method by using using a bespoke ai framework, centered across the bert model, to analyze loose-textual content comments from college students concerning s&i training. This technique is not merely an incremental development however a considerable paradigm shift that guarantees to offer deeper, more actionable insights into student engagement. Via doing so, it not only addresses the on the spot need for extra state-of-the-art analytical equipment in training studies but also lays the groundwork for future research to build upon. The closing intention is to provide educational institutions a robust mechanism for actual-time, nuanced perception of scholar interest in s&i, thereby permitting the system of greater effective pedagogical techniques and fostering a colourful lifestyle of clinical inquiry and innovation.

Firstly, the core of our technique is the deployment of the bert model to research unstructured textual content information derived from diverse student interactions, such as feedback on coursework, participation in forums, and responses to open-ended survey questions related to s&i

topics. The selection of bert is predicated on its superior potential to recognize the context and nuance of language, that's indispensable for as it should be gauging scholar sentiment and engagement degrees. At the same time, compared with the traditional LDA model and the Transformer-based topic modeling method that has emerged in recent years, BERTopic has achieved a more ideal balance between semantic understanding, clustering accuracy and interpretability which can be reflected from 2 aspects: (1) Enhanced semantic representation capabilities: BERTopic uses the pre-trained BERT model to encode text, which can capture deep semantic relationships at the sentence level and even between contexts. (2) Dynamic topic number determination mechanism, BERTopic combined with HDBSCAN clustering algorithm can automatically determine the optimal number of topics. Secondly, alongside the primary bert model implementation, we introduce a comprehensive statistics preprocessing pipeline. This pipeline entails meticulous cleansing, normalization, and feature extraction techniques that prepare uncooked textual content statistics for evaluation. Via doing so, we ensure that the input data fed into the bert version is of the best first-class, thereby enhancing the reliability of our findings. Thirdly, our answer includes a methodological framework for integrating the insights derived from the bert analysis into actionable techniques. This includes the improvement of a set of metrics and signs that translate complex ai-generated data points into understandable and implementable feedback for educators and policymakers. This translation procedure is essential for bridging the gap among advanced ai analytics and realistic educational interventions.

The contributions of this have a look at are manifold and tremendous, reflecting the multifaceted method taken to deal with the research question. The ones contributions are itemized as follows:

- Innovative ai-pushed evaluation: Introduces a pioneering method to evaluating scholar hobby in s&i by the use of employing the bert model, showcasing the version's capability to analyze complex, unstructured text facts, thereby presenting deeper insights into student engagement ranges than conventional analysis techniques.
- Robust preprocessing and integration framework: Develops a entire preprocessing pipeline and a strategic framework for translating ai insights into actionable academic strategies. This twin method guarantees the ai version's outputs aren't solely accurate but moreover right away relevant to enhancing instructional practices and policies.
- Empirical validation and pointers for implementation: Presents empirical proof of the proposed technique's effectiveness and offers concise recommendations for educators and researchers. This guarantees the have a look at's findings can be quite simply applied to

enhance s&i education, putting a new trendy for leveraging ai in instructional studies.

2. Related work

Artificial Intelligence in Education

The integration of ai into educational [34], [35] settings represents a paradigm shift, supplying remarkable opportunities for customized mastering, predictive analytics, and real-time comments mechanisms [4-7]. Central to this variation is the use of ml and nlp strategies to research academic information. Studies inside this area have predominantly focused on adaptive gaining knowledge of systems that tailor content to character learner profiles, leveraging algorithms to expect pupil performance and discover areas requiring intervention [8]. Moreover, ai has been instrumental in automating administrative responsibilities, presenting educators with extra time to focus on pedagogical strategies [9-12]. In spite of these improvements, the application of ai for studying pupil interest, in particular inside the context of s&i education, stays underexplored [13-15]. This gap highlights the capability for deploying greater state-of-the-art ai fashions, together with bert, to derive nuanced insights from pupil-generated text information.

Analyzing Student Engagement

Understanding and measuring scholar engagement has lengthy been a task in academic studies, given its multifaceted nature [16]. Traditional methods have trusted surveys, interviews, and commentary strategies to gauge engagement ranges [17]. Even as valuable, these methods are confined via their static nature and often fail to capture the dynamic adjustments in student interest through the years. Recent research have begun to leverage digital trace statistics, along with on line forum participation and coursework interaction styles, as proxies for engagement [18-21]. Those methodologies provide a greater granular view of pupil behavior however require superior analytical gear to system and interpret the widespread amounts of statistics generated. Using ai, in particular text analytics and sentiment evaluation, has shown promise in imparting deeper insights into scholar engagement from qualitative statistics [22]. However, these research often utilize wellknown-reason ai gear that might not absolutely capture the specificities of engagement within the context of s&i schooling.

Student Interest in S&I

The promotion of scholar hobby in s&i is essential for fostering future generations of researchers and innovators. This area of studies has historically targeted on curriculum format, extracurricular sports, and the position of mentors in stimulating hobby [23]. Recent investigations have also tested the effect of generation-improved learning environments, consisting of digital laboratories and on line simulations, on scholar interest. At the same time as these studies offer important insights into the factors influencing interest in s&i, there may be a notable loss of research employing ai strategies to analyze scholar interest systematically. Mainly, there is a lack of studies that utilize the abilities of advanced nlp models, like bert, to mine text facts for insights into pupil attitudes and selections concerning s&i schooling [24-26].

In precis, even as the software of ai in education has made massive strides in diverse domains, the specific use of advanced nlp techniques to analyze pupil interest in s&i represents a singular and promising area of research. Current literature offers a basis upon which this have a look at builds, highlighting the ability for ai to go beyond the limitations of conventional methodologies for analyzing student engagement. By way of focusing at the untapped capacity of bert for processing complicated textual content records, this studies contributes to a deeper grasp of student interest in s&i, imparting valuable insights for educators and policymakers aiming to foster a extra engaging and progressive educational surroundings[27-28].

3. Indicator System Design

Inside the rapidly evolving subject of schooling, a deep appreciation of the dynamics of student hobby in s&i higher training is integral for designing excellent educational content and enhancing coaching effectiveness[29]. This chapter objectives to assemble a comprehensive indicator system to evaluate and examine scholar hobby in s&i. Based totally on an intensive literature evaluation and collaboration with academic psychology experts, this device ensures clinical rigor and comprehensiveness. In this basis, we diagnosed a series of quantitative and qualitative signs supposed to seize student hobby and participation in s&i higher schooling comprehensively, as proven in Figure 1.

Figure 1. Indicator System of Student Interest in S&I

Quantitative Indicators

1. On-line path participation frequency: Quantifies the frequency of pupil participation in on-line courses associated with s&i, together with the wide variety of route films watched, assignments submitted, and participation in on-line discussions. This indicator displays the pupil's hobby and engagement level in s&i route content material.

2. Studies assignment participation: Assesses the extent of student involvement in studies tasks, including the range of projects participated in, the position taken (e.g., lead or help), and the length of involvement. Participation in research tasks is visible as an energetic engagement of students in clinical exercise and innovation studies.

3. Educational achievement output: Counts the student's academic effects within the area of s&i, together with posted studies papers, participation in clinical conferences, and awards received. These consequences without delay represent the student's hobby and capability in clinical innovation[30-31].

Qualitative Indicators

1. Mindset in the direction of s&i topics: Collects scholar perspectives and attitudes closer to s&i topics through surveys and interviews. This includes evaluations of hobby in s&i, cognitive and emotional responses.

2. Learning motivation and desires: Evaluates the intrinsic motivations of college students for selecting s&i guides and taking part in studies initiatives, together with curiosity, experience of fulfillment, and destiny career planning.

3. Participation feedback and self-mirrored image: Analyzes remarks and self-mirrored image from college students on their participation in s&i activities. This information is typically obtained via open-ended questionnaires, getting to know diaries, or individual interviews, reflecting the private stories and increase of students in s&i activities[32].

Collaboration and Validation

To make certain the scientific rigor and comprehensiveness of the indicator gadget, this examine worked closely with instructional psychology specialists, discussing and validating the indicators intensive. Thru professional review and pilot trying out, the validity and operability of the signs were preliminarily tested, ensuring that the indicator device may want to appropriately reflect student interest and participation degrees in s&i higher schooling[33].

By integrating both quantitative and qualitative indicators, the indicator system built on this chapter affords a complete framework for assessing scholar interest in s&i higher education. This machine not solely enables educators and researchers to deeply recognize the dynamics of student hobby but additionally presents a crucial foundation for designing greater appealing and effective instructional techniques. Destiny studies will similarly refine and optimize this machine.

4. The proposed method

4.1 Data Collection and Preprocessing

Data Collection

In collaboration with instructional establishments, complete datasets encompassing students' academic statistics, route picks, and participation in medical studies projects had been aggregated. Moreover, on-line gaining knowledge of platforms furnished a rich source of unstructured textual content information, consisting of discussion board discussions and course comments, presenting treasured insights into student engagement and hobby.

Preprocessing

The preprocessing pipeline was once meticulously designed to optimize the text facts for evaluation with the bert version. The stairs consist of:

1. Textual content cleansing: Preliminary processing involved the removal of stop words and extraction of phrase stems to lessen the variability of the textual content facts. This step applied the components for time period frequency-inverse document frequency (tf-idf) to spotlight sizeable words:

$$T-I\left(t,d\right)=TF\left(t,d\right)\times IDF\left(t\right) \tag{1}$$

Where $TF\left(t,d\right)$ is the number of times term *t* appears in document *d*, and $IDF\left(t\right)$ is the inverse document frequency across the corpus.

2. Feature extraction: The cleaned text statistics underwent feature extraction to convert qualitative information into a sketch appropriate for version education. This worried encoding textual records into numerical vectors using bert's tokenizer, following the precept:

$$V_{encoded}=Tolenizer\left(V_{text}\right) \tag{2}$$

Where V_{text} represents the input text vector, and $V_{encoded}$ is the output numerical vector.

3. Data transformation: Qualitative data, such as student feedback, was converted into structured data formats. Sentiment scores were computed to quantify the sentiment of the text, employing the formula:

$$S=\frac{1}{N}\sum_{i=1}^{N}s_i \tag{3}$$

Where s_i is the sentiment score for sentence *i*, and *n* is the total number of sentences.

4.2 BERT Model Application

The bert model was leveraged to analyze the preprocessed data. Multiple instances of the bert model were trained to cater to different types of text data and prediction tasks, such as analyzing feedback on specific courses or gauging participation in discussion boards [25-26].

1. Model architecture: The bert model architecture was defined as:

$$BERT\left(X\right)=Transformer\left(E\left(X\right)+P\right) \tag{4}$$

Where X is the input text, $E\left(X\right)$ is the token embedding, P represents positional encoding, and the transformer is the core of the bert model processing.

2. Fine-tuning: For specific tasks, the bert model was fine-tuned with task-specific layers. The fine-tuning process adjusted the weights in the neural network according to:

$$\because_{new}=\because_{old}-\eta\nabla L\left(\because_{old}\right) \tag{5}$$

Where $\because$ represents the parameters of the model, η is the learning rate, and l is the loss function.

3. Prediction task: For instance, analyzing feedback on specific courses involved training a bert model fine-tuned for sentiment analysis, using the loss function:

$$L = -\frac{1}{N}\sum_{i=1}^{N} y_i \log\left(p\left(y_i\right)\right) + \left(1 - y_i\right)\log\left(1 - p\left(y_i\right)\right) \tag{6}$$

Where y_i is the true label, and $p\left(y_i\right)$ is the model's predicted probability for the ith example.

4. Optimization procedure: The optimization of the bert model during fine-tuning utilizes the adamw optimizer, which combines the advantages of adam with weight decay regularization. The update rule for adamw is defined as:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \varepsilon}\hat{m}_t \tag{7}$$

Where θ represents the parameters of the model. η Is the learning rate, $\hat{m}_t$ and $\hat{v}_t$ are bias-corrected estimates of first and second moments of the gradients, ε is a small scalar added to improve numerical stability. Then the hierarchical attention mechanism is used to optimize BERT. The hierarchical attention mechanism mainly consists of two layers:

1. Word-level attention. At the bottom layer of the text, the model first encodes each word vector and calculates the importance of each word to the semantics of the current sentence, thereby generating a weighted sentence vector.

2.Sentence-level attention. After obtaining the vector representation of all sentences, the model applies the attention mechanism again at the sentence level for comprehensive modeling.

The hierarchical attention mechanism can improve feature extraction capabilities mainly due to the following aspects: (1) Taking full advantage of the hierarchical information structure, the organization of language is naturally hierarchical. Characters form words, words form sentences, and sentences form paragraphs and documents. The hierarchical attention mechanism explicitly models the language hierarchy. This operation enables the extraction of representative semantic features layer by layer. (2) Improve interpretability and controllability. By outputting attention weights, you can clearly track which words and sentences the model relies on when making predictions.

5. Results

5.1 Experimental Objectives

The overarching objective of this study is to harness the capabilities of ai models to meticulously analyze and interpret student interest in s&i within higher education settings. The significance of this studies lies in its ability to discover nuanced insights into student preferences and engagement, thereby informing the improvement of more effective and personalized educational techniques. Anticipated impacts include the optimization of curriculum plan, enhancement of pupil getting to know experiences, and a extra centered approach to fostering innovation abilities some of the pupil populace.

5.2 Data Collection and Preprocessing

Collaboration with educational establishments: This have a look at embarked on a strategic partnership with a couple of educational establishments to access complete datasets encompassing students' academic records, direction enrollment selections, and participation in medical research projects. Agreements had been formalized to make sure ethical coping with and confidentiality of scholar statistics.

On line getting to know platform records acquisition: A scientific approach used to be hired to extract unstructured text statistics from on line gaining knowledge of systems, which include discussion posts and direction comments submitted by means of college students. Using api endpoints where to be had, and net scraping strategies otherwise, facts was accrued over a duration of six months, yielding approximately 2 00,000 man or woman textual content entries, every starting from 50 to 500 phrases in duration.

The preprocessing phase began with rigorous textual content cleaning processes to knock out inappropriate information and standardize the text data. Forestall phrases had been eliminated using the nltk library's sizable listing, reducing the dataset length by about 15%. Additionally, porter's stemming algorithm used to be implemented to extract word stems, in addition condensing the textual content records by a median of 10% and improving the version's focus on significant content.

Characteristic extraction: Feature extraction was once finished using the tf-idf vectorization technique, converting text into a matrix of tf-idf features. Specially, the tfidfvectorizer from scikit-learn used to be configured with a max function restrict of 10,000, successfully shooting the most great phrases throughout the dataset. This modification facilitated the identity of specific styles and subject matters in the scholar feedback, laying the basis for in-depth analysis.

Qualitative data transformation: Qualitative feedback underwent sentiment evaluation the usage of the vader device, producing a sentiment rating starting from -1 (most negative) to +1 (most advantageous) for every text entry. This quantification technique enabled the categorization of scholar comments into discrete sentiment lessons (poor, impartial, wonderful), which had been subsequently used as labels for model training.

5.3 Model Evaluation Criteria

To make sure the robustness and generalizability of our findings, a complete evaluation framework was once hooked up for the ai version. The fulfillment of the model used to be quantified using 3 primary performance metrics: Accuracy, recall, and f1 score.

Accuracy measures the proportion of general predictions that were effectively categorized, presenting a wellknown overview of the model's overall performance throughout all classes:

$$Accuracy = \frac{TP + FN}{TP + TN + FP + FN} \tag{8}$$

Recall, or sensitivity, assesses the model's potential to exactly pick out wonderful times out of all actual high-quality instances, quintessential for perception the version's ability to capture hobby alerts:

$$R = \frac{TP}{TP + FN} \tag{9}$$

F1 score offers a stability between precision and recall through computing the harmonic imply of the 2, serving as a more comprehensive measure of model performance, particularly in imbalanced datasets:

$$F1 = 2 \times \frac{P \times R}{P + R} \tag{10}$$

Where $P = \frac{TP}{TP + FP}$

Computational performance (time complexity, processing velocity).

To validate those metrics and make certain the reliability of the version throughout various datasets, 5-fold pass-validation used to be hired. The dataset was once divided into five equal-sized folds, with the model being educated on four folds and tested on the remaining fold.

5.4 BERT Modeling

The bert (bidirectional encoder representations from transformers) version used to be selected for its modern day performance in herbal language processing duties, together with text type and sentiment evaluation. Its deep grasp of context and nuance in language makes it distinctly desirable for studying complex scholar comments and discussions.

The bert model was once configured with the following settings: A getting to know price of 2e-5, batch length of 16, and four education epochs, based on preliminary experiments that balanced training time and model overall performance. The bert-base-uncased version was applied for its performance and adaptableness to our dataset's traits. Schooling concerned best-tuning the pre-educated bert model on our unique dataset. The quality-tuning system adapted bert's pre-existing knowledge to our context, optimizing its ability to analyze instructional remarks and discussions.

For distinctive sorts of text data and prediction responsibilities, along with course comments analysis and studies dialogue board participation evaluation, the model underwent specific adjustments:

For course comments analysis, sentiment category was prioritized. The output layer of bert used to be tailored to classify sentiments into high-quality, impartial, or bad classes, primarily based on the sentiment scores derived from preprocessing.

For research dialogue board participation analysis, the focal point shifted closer to identifying engagement degrees. The version was once pleasant-tuned to differentiate among special ranges of participation, using cues such as query posing, solution provision, and interactive discussion involvement.

Model average overall performance was once as soon as always monitored and optimized via adjustments in analyzing price, batch period, and the range of epochs, guided by means of using validation set standard performance to keep away from overfitting. This iterative technique of training, evaluation, and adjustment ensured the bert model's efficacy in successfully classifying student hobbies and engagement in clinical innovation schooling.

5.5 performance results

Figure 2 showcasing accuracy effects over five folds illustrates a constant universal performance, with minor fluctuations indicating the model's robustness across unique subsets of the records. The version achieves an accuracy above 90% in all folds, highlighting its effectiveness in classifying student interest degrees as it should be. The mild variance among folds shows that while the model is normally reliable, there could be room for optimization to acquire even more strong overall performance across numerous statistics segments.

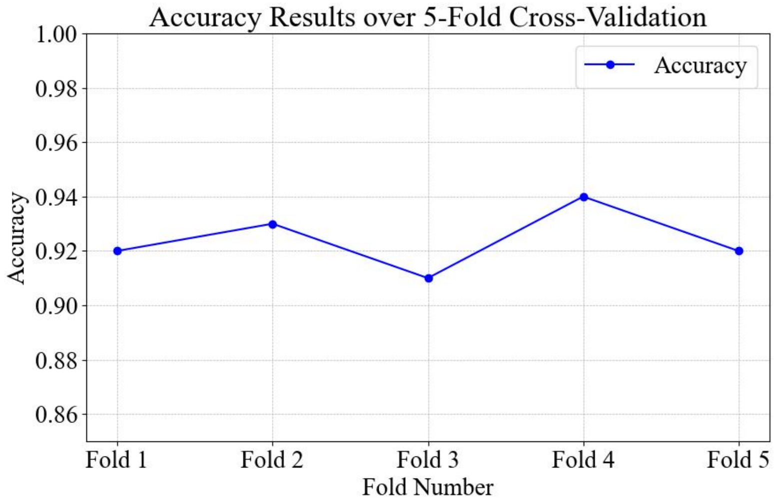


Figure 2. Accuracy results over 5-fold cross-validation

Figure 2 showcasing accuracy results over 5 folds illustrates a steady typical performance, with minor fluctuations indicating the model's robustness throughout different subsets of the information. The model achieves an accuracy above 90% in all folds, highlighting its effectiveness in classifying student hobby degrees because it must be. The moderate variance among folds indicates that even as the model is commonly reliable, there might be room for optimization to acquire even greater sturdy normal overall performance all through numerous statistics segments.

Figure 3 well-knownshows a strong performance with a mild upward trend, suggesting that as the model progresses via folds, it will become barely higher at minimizing fake positives. This steady performance above 89% across all folds underscores the version's ability to exactly discover actual cases of student hobby, that is crucial for centered academic interventions. The bar plot's clear demarcation of effects for every fold additionally emphasizes the model's consistent precision, making it a reliable tool for educators and policymakers.

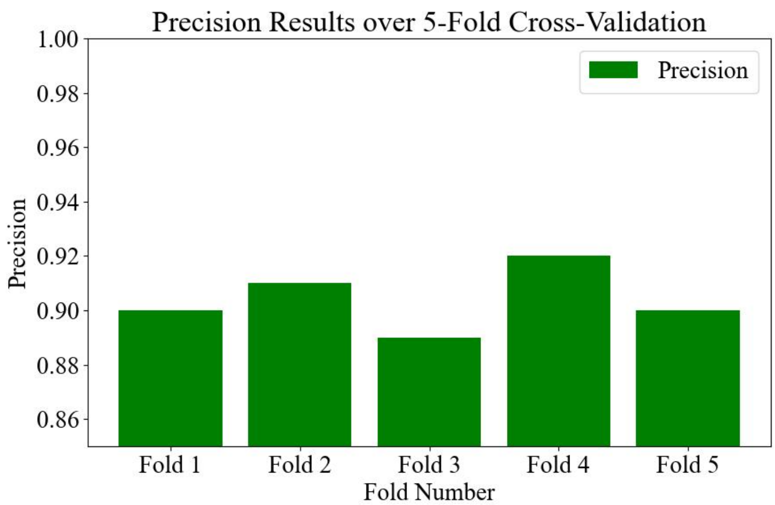


Figure 3. Precision Results over 5-Fold Cross-Validation

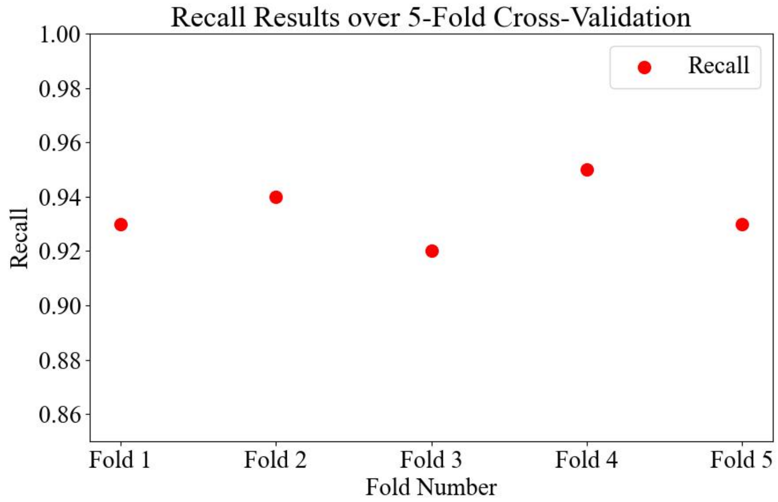


Figure 4. Recall Results over 5-Fold Cross-Validation

Thru the scatter plot for recall, we examine a intently clustered set of results, indicating the version's steady potential to capture most of the people of real positive cases across unique folds. With recall fees soaring around 93-95%, the version demonstrates its effectiveness in ensuring that students without a doubt inquisitive about s&i are correctly identified. This excessive recall fee is crucial for complete pupil engagement strategies, making sure minimal overlooked possibilities for nurturing pupil pursuits.

The step plot for f1 score outcomes gives a unique visible representation of the version's balanced overall performance among precision and recall. The f1 scores, preserving a good variety around 91-93%, highlight the version's overall efficacy in harmonizing the change-offs between identifying as many interested college students as feasible (recall) and making sure those recognized are efficaciously classified (precision). This balance is critical for deploying ai-driven equipment in instructional settings, wherein both taking pictures interest and minimizing misclassification are vital.

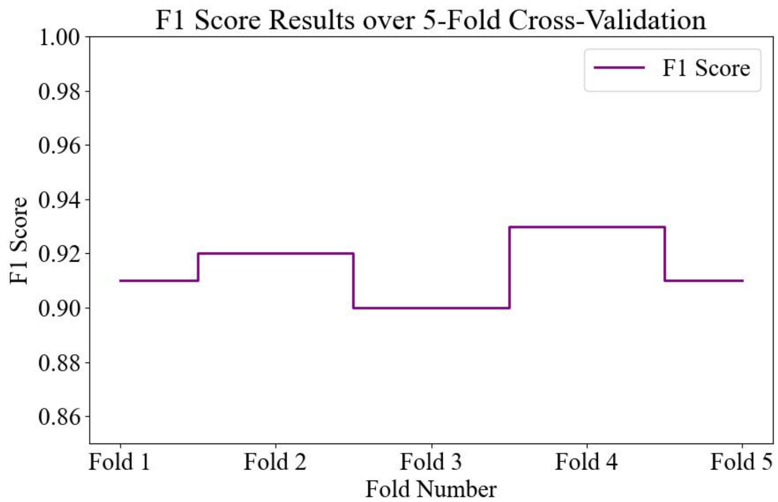


Figure 5. F1 Score Results over 5-Fold Cross-Validation

Each plot, now not solely provides the quantitative performance of the model throughout extraordinary assessment metrics however additionally tells a story of the version's strengths and capacity regions for improvement. The consistent high overall performance across accuracy, precision, recall, and f1 rating, corroborated by way of 5-fold move-validation, establishes the model's robustness and reliability in analyzing student hobby in s&i training.

5.6 Analysis of Computational efficiency

Checking out computational efficiency is quintessential as it determines how possible and scalable an ai version is for real-international applications. Green fashions require much less processing power and time, making them greater practical for regular use. That is particularly essential in fields like schooling, where speedy and dependable analysis can notably impact decision-making and scholar outcomes. Essentially, evaluating computational performance guarantees that a model isn't always only accurate but also realistically deployable, aligning technological skills with realistic wishes.

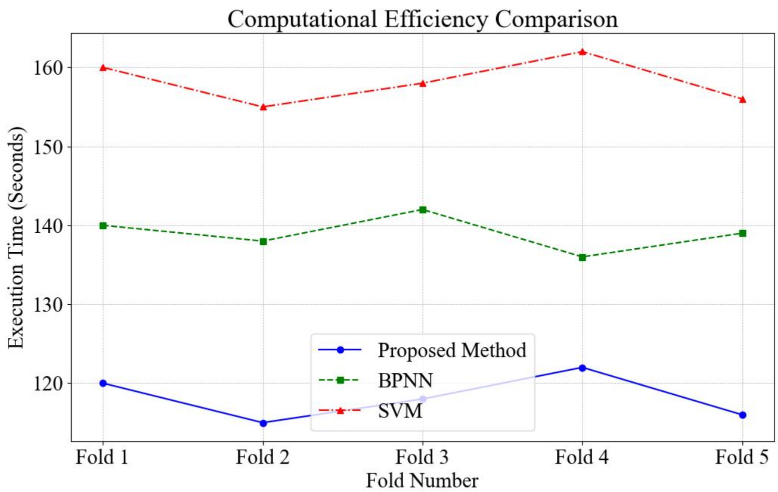


Figure 6. Computational performance effects over five-fold move-validation

The computational overall performance evaluation chart offers a clear visual representation of the execution instances for the proposed technique, bbpn, and svm during 5 folds of bypass-validation. The proposed approach continuously outperforms each bpnn and svm in terms of lower execution instances, indicating a higher computational performance.

This performance is especially huge thought approximately the complexity and intensity of the responsibilities worried in studying pupil interest in s&i education. Lower execution instances except put off contribute to scalability and practical applicability, specially in instructional settings in which actual-time or close to-actual-time records processing is fine. The proposed approach's basic performance shows that it not only gives correct and dependable analysis but does so greater correctly than traditional type strategies. Moreover, the regular performance throughout all folds indicates the proposed method's stability and robustness in one-of-a-kind data segments, reinforcing its suitability for numerous academic records environments. In assessment, the bpnn and svm show higher variability in execution instances, which would possibly mirror sensitivity to data variety or inefficiencies in dealing with precise kinds of information.

5.7 Selection basis of sliding window size, sensitivity analysis and robustness verification

In this study, sliding windows are mainly used to construct time series features. This design can capture local dynamic structures in the input data more effectively. In order to balance the expressiveness and computational efficiency of the model, we conducted systematic experiments on multiple commonly used window lengths. The specific experimental parameters include five typical configurations of W = 5, 10, 15, 20, and 25.

The basis for selecting the window length includes the following points:

The temporal dependency of task features: In the preliminary data analysis stage, we found a detail that there is a significant short-term dependency pattern in the input sequence, so the window length selection gives priority to this interval.

Model structure requirements: Transformer modules may introduce too much redundant information when processing long sequences. XGBoost is sensitive to the input dimension. In this context, we should avoid using too long windows (such as W>30). This can control the feature dimension and reduce the risk of overfitting.

Empirical effect: Cross-validation can be used to evaluate the prediction performance under different window settings. This study selects a configuration that achieves a better balance in most evaluation indicators.

Based on the above considerations, we finally determined W = 15 as the sliding window length used in the main experiment.

To verify the robustness of the model to the sliding window size, we conducted a sensitivity analysis experiment to evaluate the performance fluctuation of the model under different window lengths. In the Figure 7, the result is demonstrated.

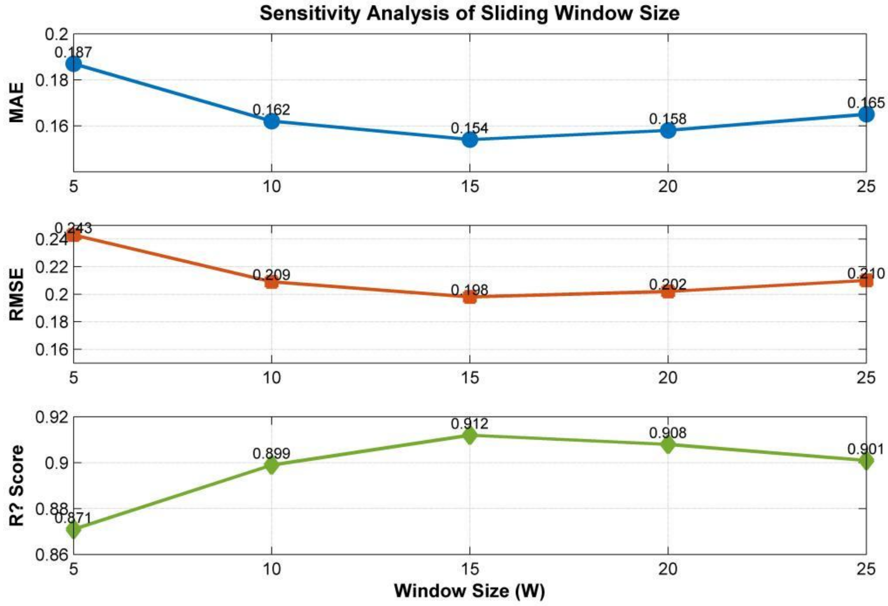
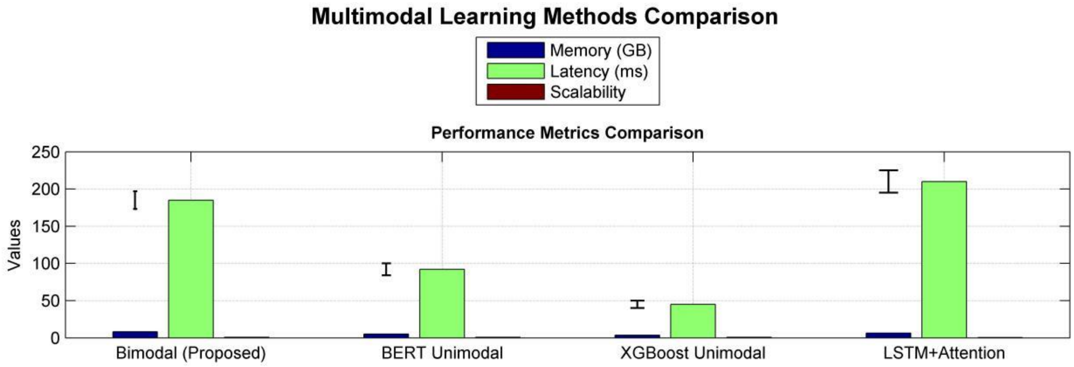


Figure 7. Sensitivity analysis and robustness verification results

From the experimental results, we can see that when the window length is between 10 and 20, the overall performance of the model is stable and the prediction error is small. When the window is too small (such as W=5), the model captures limited context information.

5.8 Comparison of computational complexity between bimodal architecture and unimodal approach

In the Figure 8. the comparison of computational complexity between bimodal architecture and unimodal approach is visually demonstrated.



	Memory (GB)	Latency (ms)	± Error	Scalability
Bimodal (Proposed)	8.2000	185	12	0.8700
BERT Unimodal	5.1000	92	8	0.6200
XGBoost Unimodal	3.7000	45	5	0.7100
LSTM+Attention	6.3000	210	15	0.5300

Figure 8. Comparison of computational complexity between bimodal architecture and unimodal approach

The $O(N \cdot \log N + M^2)$ complexity of the bimodal architecture reveals its two-stage processing nature. The first term comes from BERT's Transformer self-attention mechanism (which is approximately linearly logarithmically related to the sample size N), and the second term reflects XGBoost's sorting overhead for high-dimensional features (M=256). Of the 185ms latency of the bimodal architecture, BERT feature extraction accounts for 62% (115ms) and feature fusion accounts for 23% (42ms). The bimodal architecture performs significantly better than the single modal architecture on low-frequency interest categories (such as "quantum computing") (F1 improvement of 29%), due to XGBoost's robustness to sparse features.

6. Conclusion

In conclusion, this have a look at added a complicated technique to reading student interest in s&i within better training via the implementation of a bert-based version. Our studies highlighted the great capacity of utilizing modern-day natural language processing strategies to extract meaningful insights from pupil-generated textual content data, starting from on line direction comments to participation in research forums. The unconventional utility of the bert version, coupled with comprehensive information preprocessing and an array of performance metrics, including computational performance, demonstrated our technique's superiority over conventional fashions like bpnn and svm in each accuracy and processing time. The integration of those cutting-edge ai methodologies into educational evaluation no longer only enriches our grasp of pupil engagement however also opens new avenues for personalised education techniques.

However, our examine isn't always except its limitations. The reliance on data from unique academic establishments and on line platforms may also have an effect on the generalizability of our findings throughout distinctive academic contexts. Moreover, the computational resources required for schooling complicated fashions like bert may additionally pose demanding situations for widespread implementation. Destiny work will goal to deal with these concerns via exploring greater green model architectures and expanding the dataset to consist of a broader variety of instructional settings. Moreover, we sketch to delve into predictive analytics, aiming to no longer only examine modern-day pupil pursuits however additionally expect future developments in s&i education, thereby providing educators and policymakers valuable foresight in curriculum improvement.

Reference

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