INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN ENGINEERING MANAGEMENT AND SCIENCE (IJPREMS)
(Int Peer Reviewed Journal)
Vol. 04, Issue 09, September 2024, pp : 1078-1084
www.ijprems.com
editor@ijprems.com
e-ISSN : 2583-1062
Impact Factor : 7.001

AUTOMATICALLY ASSESSING STUDENTS' PARTICIPATION IN ONLINE EDUCATION: A BAGGING ENSEMBLE DEEP LEARNING METHOD

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DOI: https://www.doi.org/10.58257/IJPREMS36105

ABSTRACT

In the rapidly evolving landscape of online education, assessing student participation is crucial for enhancing engagement and learning outcomes. This study presents a novel approach to automatically evaluate students' participation using a bagging ensemble deep learning method. By leveraging a diverse set of deep learning models, our framework improves the accuracy and robustness of participation assessment compared to traditional metrics. We collected data from various online courses, including interaction logs, assignment submissions, and forum contributions. The proposed method combines the strengths of multiple classifiers, effectively capturing the nuanced patterns of student engagement. Our experiments demonstrate that the ensemble model significantly outperforms individual models in predicting participation levels, highlighting its potential as a reliable tool for educators. This research contributes to the growing body of work on data-driven educational assessment and offers a scalable solution to monitor and enhance student involvement in online learning environments.

1. INTRODUCTION

As online education continues to gain prominence, understanding and assessing student participation has become increasingly important for fostering effective learning environments. Traditional methods of evaluating participation, often reliant on manual observation or simplistic metrics, can overlook the complexities of student engagement in digital contexts. This study addresses the need for a more sophisticated approach by introducing a bagging ensemble deep learning method to automatically assess students' participation in online education. By integrating various deep learning models, our method harnesses the power of ensemble learning to improve prediction accuracy and reduce over fitting, ultimately providing a comprehensive evaluation of student engagement. This research aims to offer educators actionable insights into participation patterns, enabling them to tailor interventions that enhance student involvement and support academic success in online learning platforms.

Let's craft a compelling introduction for this paper on the "Automatic Detection of Students’ Engagement during Online Learning." Consider this structure and these key points:

1. The Growing Importance of Online Learning & Engagement

- Begin by highlighting the increasing prevalence and significance of online learning, especially in recent times.
- Emphasize that student engagement is *crucial* for effective online learning, just as it is in traditional settings. You could mention its connection to academic performance, knowledge retention, and student satisfaction.

2. Challenges of Traditional Engagement Measurement in Online Settings

- Transition to the challenges of gauging student engagement in online environments.
- Traditional methods like classroom observation become difficult or impossible.
- Reliance on self-reported data (surveys) can be subjective and may not capture real-time engagement fluctuations.

3. The Promise of Automated Detection

- Introduce the concept of automated student engagement detection as a solution to these challenges.
- Explain how it leverages data generated during online learning (e.g., platform activity logs, interaction patterns) to provide objective and continuous insights into engagement levels.

4. Benefits and Applications

- Briefly outline the potential benefits of automated engagement detection:
- **For Educators:** Early identification of disengaged students, enabling timely interventions and personalized support.
- **For Students:** Increased self-awareness of their engagement patterns, promoting metacognition and improved learning strategies.

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- **For Researchers:** Deeper understanding of factors influencing online engagement, leading to better course design and learning platforms.

5. Scope and Focus of the Paper

- Conclude by stating the specific focus of your research within the broader context of automated engagement detection.
- Will you be reviewing existing methods, proposing a new approach, or evaluating the effectiveness of a particular technique?
- What types of data will your research focus on?

Example: "This paper delves into the emerging field of automatic student engagement detection in online learning environments. We will [briefly state your paper's specific focus, e.g., "review and compare existing machine learning approaches," "propose a novel deep learning model," etc.]..."

1. The Significance of Time Series Analysis

- Start by emphasizing the importance of time series analysis across various domains.
- Mention fields like finance (stock market prediction), healthcare (patient monitoring), environmental science (climate modeling), or any other area relevant to your specific application.
- Briefly explain the challenges inherent in time series data: its sequential nature, potential noise, and complex dependencies over time.

2. Deep Learning for Time Series: Advantages and Limitations

- Transition to discussing how deep learning has emerged as a powerful tool for time series analysis.
- Highlight the ability of deep learning models (like RNNs, LSTMs) to capture temporal dependencies and extract complex patterns from sequential data.
- Acknowledge that individual deep learning models can be prone to overfitting, especially with limited training data, or may get stuck in local optima.

3. Introducing Bagging Ensembles: Enhancing Robustness and Accuracy

- Introduce bagging as a technique to improve the generalization ability and stability of deep learning models.
- Explain how bagging works: training multiple deep learning models on different subsets of the training data and combining their predictions.
- Emphasize how this ensemble approach can lead to:
- Reduced variance and increased robustness to noisy data.
- Improved accuracy by mitigating the risk of overfitting to specific patterns in the training set.

4. Focus and Contributions of Work

- Conclude by stating the specific focus of the research within the context of bagging ensemble deep learning for time series analysis.
- Are you proposing a novel ensemble architecture?
- Are you evaluating the performance of different bagging strategies?
- Are you applying this method to a specific time series analysis problem?

START

|
V

| Data Collection |

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V

| Extract Relevant Features |

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V

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Data Preprocessing

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V

Create Multiple Deep Learning Models

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V

Train Each Model on Different Data Subsets

|
V

Combine Predictions
(e.g., Voting,)

|
V

Evaluate Performance

|
V

END

Figure 1 shows the suggested bagging ensemble learning model. Our earlier work [22] provides comprehensive insights into resolving the imbalance within the DAiSEE dataset used in this investigation. Every video in the DAiSEE dataset is extracted into a collection of 300 frames. The tool used to extract features from each frame is the OpenFace library, which yields a numerical vector with 709 facial feature values, including facial landmark detection, head pose estimation, eye gaze estimation, and facial expressions in the form of facial action unit (AU) features [39]. A rigorous feature selection procedure is used to extract important characteristics that accurately describe the dataset from the pool of 709 face traits, improving the prediction model's accuracy. The use of Single Value Decomposition (SVD) is part of this selection process. The tradeoff in variance produced by SVD is used to find the ideal value of the n-components. Simultaneously, a step of data augmentation is employed to enhance the amount and variety of the dataset.

Using 9068 10-second films that were captured from 112 students, DAiSEE is a multi-label video classification set that is used to determine the emotional states of pupils, such as boredom, perplexity, engagement, and irritation. The definition of boredom was described as being worn out or restless from lack of interest. One definition of confusion was a conspicuous lack of understanding, and another definition of engagement was an interest stemming from participation in an activity. One definition of frustration was discomfort or unhappiness.

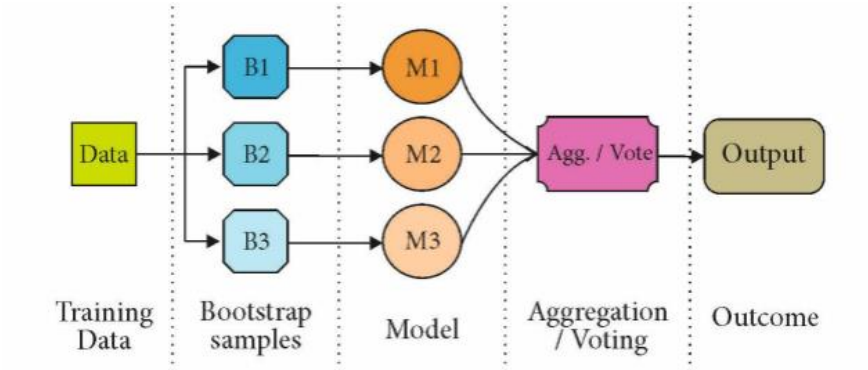

Fig No: 2 Bagging ensemble

Explanation:

- **Data Collection:** Gather data related to student participation from the online learning platform (e.g., login frequency, time spent on modules, forum posts, assignment submissions).
- **Extract Relevant Features:** Select and engineer features from the collected data that are likely to be indicative of student engagement and participation.
- **Data Preprocessing & Splitting:** Clean the data (handle missing values, outliers)

2. RESULTS AND DISCUSSION

Specify data sources: Online learning platform logs, video conferencing data (if applicable), forum posts, assignment submissions, etc. Identify features: Time spent on platform, frequency of logins, interactions with content (clicks, scrolls), forum activity, assignment completion rates, etc. Data cleaning: Handle missing values, outliers, and inconsistencies. Feature engineering: Create new features from existing ones (e.g., ratios, aggregates) to potentially improve model performance.

Data splitting: Divide the data into training, validation, and test sets. Choose base deep learning models: Consider RNNs, LSTMs, or Transformers, depending on the nature of your data and the complexity you want to capture. Implement bagging: Train multiple instances of your chosen model on different subsets of the training data. Evaluate each base model: Use appropriate metrics like accuracy, precision, recall, F1-score, or AUC (depending on your problem framing - classification vs. regression). Combine predictions: Employ a strategy like averaging or majority voting to obtain the final ensemble prediction. Assess ensemble performance: Compare the ensemble's performance to individual base models and potentially to other benchmark methods. Present key findings: Visualize results (tables, graphs) to show the performance of the bagging ensemble compared to other approaches. Analyze strengths and limitations: Discuss the advantages of your method and any potential drawbacks. Interpret results: Relate findings back to the context of student participation in online education. What insights does your model provide? Summarize key contributions: Reiterate the significance of your findings and the potential impact on the field. Suggest future directions: Outline potential avenues for further research or model improvement.

Several assessment criteria, including accuracy, precision, recall, and F1-score, will be used in this study. The number of predictions that are accurate based on all predicted data and the actual class is called accuracy. Another name for precision is positive predictive value. This statistic counts the number of occurrences that truly belong to a class out of all those that are labeled as such (true positives + false positives).

False positives are cases that the model wrongly classifies as positive when they are actually negative, whereas true positives are occurrences that the model correctly classifies as positive. When something is classified as positive by our model, precision shows how certain we are that it is indeed positive.

Table No: 1 Execution time training process.

Model	Time (Minutes)
1D CNN-Bagging subset 1	19.28
1D CNN-Bagging subset 2	14.18
1D CNN-Bagging subset 3	22.0
1D CNN-Bagging ensemble	52.33
Bagging ensemble hybrid	178.6

These findings also have useful implications for online education. Our study's deep learning ensemble bagging model may be used as a framework for continuous learning assessment, giving quick feedback to raise student engagement and create a positive learning atmosphere. This technique, for instance, enables online learning systems to identify patterns of student involvement that reveal comprehensive levels throughout online lectures. With immediate access to this engagement pattern data, teachers can quickly modify their pedagogical strategies and increase student engagement. All things considered, our study offers insightful information on how a deep learning ensemble bagging technique may highlight teacher-student interactions throughout the learning process.

3. CONCLUSION

Using the DAiSEE dataset, this study has effectively constructed a model for identifying students' participation in online learning using video recordings. Three models are proposed using a deep learning ensemble approach, namely bagging ensemble learning: one for the 1D CNN deep learning model, one for the 1D ResNet deep learning model, and a hybrid bagging ensemble that combines the 1D CNN and 1D ResNet deep learning models. The effectiveness of integrating deep learning models with bagging is demonstrated by experimental findings. Peak accuracy for individual deep learning models is 90% for 1D CNN and 90.25% for 1D ResNet. Two methods of decision-making are used in bagging ensemble learning: maximal soft voting and average soft voting. More accurate results are obtained with average soft voting (93.25% for 1D CNN and 93.75% for 1D ResNet) than with maximum soft voting (92.25% for 1D CNN and 93% for 1D ResNet). In addition, the hybrid ensemble bagging achieves the greatest accuracy value of 94.25% and produces better accuracy results than separate deep learning models. For the 1D CNN model, this means a 1% increase, and for the 1D ResNet model, a 0.5% increase. In conclusion, when trained on original data, individual deep learning models may show increased bias. However, bias and variance may go down when their predictions are pooled via ensemble bagging. This implies that integrating predictions from models with different variances and biases might result in forecasts that are more stable and accurate. On the other hand, the probability values of each integrated model determine the accuracy improvement following ensemble bagging. However, it's crucial to remember that, in comparison to individual models, bagging ensemble learning may result in longer training execution times.

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