An automated essay scoring systems: a systematic literature review

Dadi Ramesh¹,² · Suresh Kumar Sanampudi³

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Abstract
Assessment in the Education system plays a significant role in judging student performance. The present evaluation system is through human assessment. As the number of teachers’ student ratio is gradually increasing, the manual evaluation process becomes complicated. The drawback of manual evaluation is that it is time-consuming, lacks reliability, and many more. This connection online examination system evolved as an alternative tool for pen and paper-based methods. Present Computer-based evaluation system works only for multiple-choice questions, but there is no proper evaluation system for grading essays and short answers. Many researchers are working on automated essay grading and short answer scoring for the last few decades, but assessing an essay by considering all parameters like the relevance of the content to the prompt, development of ideas, Coherence, and Coherence is a big challenge till now. Few researchers focused on Content-based evaluation, while many of them addressed style-based assessment. This paper provides a systematic literature review on automated essay scoring systems. We studied the Artificial Intelligence and Machine Learning techniques used to evaluate automatic essay scoring and analyzed the limitations of the current studies and research trends. We observed that the essay evaluation is not done based on the relevance of the content and coherence.

Keywords Assessment · Short answer scoring · Essay grading · Natural language processing · Deep learning

Dadi Ramesh
dadiramesh44@gmail.com

Suresh Kumar Sanampudi
sureshsanampudi@jntuh.ac.in

¹ School of Computer Science and Artificial Intelligence, SR University, Warangal, TS, India
² Research Scholar, JNTU, Hyderabad, India
³ Department of Information Technology, JNTUH College of Engineering, Nachupally, Kondagattu, Jagtial, TS, India
1 Introduction

Due to COVID 19 outbreak, an online educational system has become inevitable. In the present scenario, almost all the educational institutions ranging from schools to colleges adapt the online education system. The assessment plays a significant role in measuring the learning ability of the student. Most automated evaluation is available for multiple-choice questions, but assessing short and essay answers remain a challenge. The education system is changing its shift to online-mode, like conducting computer-based exams and automatic evaluation. It is a crucial application related to the education domain, which uses natural language processing (NLP) and Machine Learning techniques. The evaluation of essays is impossible with simple programming languages and simple techniques like pattern matching and language processing. Here the problem is for a single question, we will get more responses from students with a different explanation. So, we need to evaluate all the answers concerning the question.

Automated essay scoring (AES) is a computer-based assessment system that automatically scores or grades the student responses by considering appropriate features. The AES research started in 1966 with the Project Essay Grader (PEG) by Ajay et al. (1973). PEG evaluates the writing characteristics such as grammar, diction, construction, etc., to grade the essay. A modified version of the PEG by Shermis et al. (2001) was released, which focuses on grammar checking with a correlation between human evaluators and the system. Foltz et al. (1999) introduced an Intelligent Essay Assessor (IEA) by evaluating content using latent semantic analysis to produce an overall score. Powers et al. (2002) proposed E-rater and Intellimetric by Rudner et al. (2006) and Bayesian Essay Test Scoring System (BESTY) by Rudner and Liang (2002), these systems use natural language processing (NLP) techniques that focus on style and content to obtain the score of an essay. The vast majority of the essay scoring systems in the 1990s followed traditional approaches like pattern matching and a statistical-based approach. Since the last decade, the essay grading systems started using regression-based and natural language processing techniques. AES systems like Dong et al. (2017) and others developed from 2014 used deep learning techniques, inducing syntactic and semantic features resulting in better results than earlier systems.

Ohio, Utah, and most US states are using AES systems in school education, like Utah compose tool, Ohio standardized test (an updated version of PEG), evaluating millions of student’s responses every year. These systems work for both formative, summative assessments and give feedback to students on the essay. Utah provided basic essay evaluation rubrics (six characteristics of essay writing): Development of ideas, organization, style, word choice, sentence fluency, conventions. Educational Testing Service (ETS) has been conducting significant research on AES for more than a decade and designed an algorithm to evaluate essays on different domains and providing an opportunity for test-takers to improve their writing skills. In addition, they are current research content-based evaluation.

The evaluation of essay and short answer scoring should consider the relevance of the content to the prompt, development of ideas, Cohesion, Coherence, and domain knowledge. Proper assessment of the parameters mentioned above defines the accuracy of the evaluation system. But all these parameters cannot play an equal role in essay scoring and short answer scoring. In a short answer evaluation, domain knowledge is required, like the meaning of "cell" in physics and biology is different. And while evaluating essays, the implementation of ideas with respect to prompt is required. The system should also assess the completeness of the responses and provide feedback.
Several studies examined AES systems, from the initial to the latest AES systems. In which the following studies on AES systems are Blood (2011) provided a literature review from PEG 1984–2010. Which has covered only generalized parts of AES systems like ethical aspects, the performance of the systems. Still, they have not covered the implementation part, and it’s not a comparative study and has not discussed the actual challenges of AES systems.

Burrows et al. (2015) Reviewed AES systems on six dimensions like dataset, NLP techniques, model building, grading models, evaluation, and effectiveness of the model. They have not covered feature extraction techniques and challenges in features extractions. Covered only Machine Learning models but not in detail. This system not covered the comparative analysis of AES systems like feature extraction, model building, and level of relevance, cohesion, and coherence not covered in this review.

Ke et al. (2019) provided a state of the art of AES system but covered very few papers and not listed all challenges, and no comparative study of the AES model. On the other hand, Hussein et al. in (2019) studied two categories of AES systems, four papers from handcrafted features for AES systems, and four papers from the neural networks approach, discussed few challenges, and did not cover feature extraction techniques, the performance of AES models in detail.

Klebanov et al. (2020). Reviewed 50 years of AES systems, listed and categorized all essential features that need to be extracted from essays. But not provided a comparative analysis of all work and not discussed the challenges.

This paper aims to provide a systematic literature review (SLR) on automated essay grading systems. An SLR is an Evidence-based systematic review to summarize the existing research. It critically evaluates and integrates all relevant studies’ findings and addresses the research domain’s specific research questions. Our research methodology uses guidelines given by Kitchenham et al. (2009) for conducting the review process; provide a well-defined approach to identify gaps in current research and to suggest further investigation.

We addressed our research method, research questions, and the selection process in Sect. 2, and the results of the research questions have discussed in Sect. 3. And the synthesis of all the research questions addressed in Sect. 4. Conclusion and possible future work discussed in Sect. 5.

## 2 Research method

We framed the research questions with PICOC criteria.

*Population (P)*  Student essays and answers evaluation systems.

*Intervention (I)*  Evaluation techniques, data sets, features extraction methods.

*Comparison (C)*  Comparison of various approaches and results.

*Outcomes (O)*  Estimate the accuracy of AES systems.

*Context (C)*  NA.

### 2.1 Research questions

To collect and provide research evidence from the available studies in the domain of automated essay grading, we framed the following research questions (RQ):

*RQ1* what are the datasets available for research on automated essay grading?
The answer to the question can provide a list of the available datasets, their domain, and access to the datasets. It also provides a number of essays and corresponding prompts. 

**RQ2** What are the features extracted for the assessment of essays?  
The answer to the question can provide an insight into various features so far extracted, and the libraries used to extract those features. 

**RQ3** What are the evaluation metrics available for measuring the accuracy of algorithms?  
The answer will provide different evaluation metrics for accurate measurement of each Machine Learning approach and commonly used measurement technique.  

**RQ4** What are the Machine Learning techniques used for automatic essay grading, and how are they implemented?  
It can provide insights into various Machine Learning techniques like regression models, classification models, and neural networks for implementing essay grading systems. The response to the question can give us different assessment approaches for automated essay grading systems.  

**RQ5** What are the challenges/limitations in the current research?  
The answer to the question provides limitations of existing research approaches like cohesion, coherence, completeness, and feedback.

### 2.2 Search process

We conducted an automated search on well-known computer science repositories like ACL, ACM, IEEE Explore, Springer, and Science Direct for an SLR. We referred to papers published from 2010 to 2020 as much of the work during these years focused on advanced technologies like deep learning and natural language processing for automated essay grading systems. Also, the availability of free data sets like Kaggle (2012), Cambridge Learner Corpus-First Certificate in English exam (CLC-FCE) by Yannakoudakis et al. (2011) led to research this domain.  

**Search Strings:** We used search strings like “Automated essay grading” OR “Automated essay scoring” OR “short answer scoring systems” OR “essay scoring systems” OR “automatic essay evaluation” and searched on metadata.

### 2.3 Selection criteria

After collecting all relevant documents from the repositories, we prepared selection criteria for inclusion and exclusion of documents. With the inclusion and exclusion criteria, it becomes more feasible for the research to be accurate and specific.  

**Inclusion criteria 1** Our approach is to work with datasets comprise of essays written in English. We excluded the essays written in other languages.  

**Inclusion criteria 2** We included the papers implemented on the AI approach and excluded the traditional methods for the review.  

**Inclusion criteria 3** The study is on essay scoring systems, so we exclusively included the research carried out on only text data sets rather than other datasets like image or speech.  

**Exclusion criteria** We removed the papers in the form of review papers, survey papers, and state of the art papers.
2.4 Quality assessment

In addition to the inclusion and exclusion criteria, we assessed each paper by quality assessment questions to ensure the article’s quality. We included the documents that have clearly explained the approach they used, the result analysis and validation.

The quality checklist questions are framed based on the guidelines from Kitchenham et al. (2009). Each quality assessment question was graded as either 1 or 0. The final score of the study range from 0 to 3. A cut off score for excluding a study from the review is 2 points. Since the papers scored 2 or 3 points are included in the final evaluation. We framed the following quality assessment questions for the final study.

Quality Assessment 1: Internal validity.
Quality Assessment 2: External validity.
Quality Assessment 3: Bias.

The two reviewers review each paper to select the final list of documents. We used the Quadratic Weighted Kappa score to measure the final agreement between the two reviewers. The average resulted from the kappa score is 0.6942, a substantial agreement between the reviewers. The result of evolution criteria shown in Table 1. After Quality Assessment, the final list of papers for review is shown in Table 2. The complete selection process is shown in Fig. 1. The total number of selected papers in year wise as shown in Fig. 2.

3 Results

3.1 What are the datasets available for research on automated essay grading?

To work with problem statement especially in Machine Learning and deep learning domain, we require considerable amount of data to train the models. To answer this question, we listed all the data sets used for training and testing for automated essay grading systems. The Cambridge Learner Corpus-First Certificate in English exam (CLC-FCE)

| Table 1 | Quality assessment analysis |
|---------|-----------------------------|
|         | Number of papers | Quality assessment score |
| ---     | ---               | ---                        |
| 50      | 3                 |
| 12      | 2                 |
| 59      | 1                 |
| 23      | 0                 |

| Table 2 | Final list of papers |
|---------|-----------------------|
|         | Data base | Paper count |
| ---     | ---        | ---          |
| ACL     | 28         |
| ACM     | 5          |
| IEEE Explore | 19       |
| Springer | 5          |
| Other   | 5          |
| Total   | 62         |
Yannakoudakis et al. (2011) developed corpora that contain 1244 essays and ten prompts. This corpus evaluates whether a student can write the relevant English sentences without any grammatical and spelling mistakes. This type of corpus helps to test the models built for GRE and TOFEL type of exams. It gives scores between 1 and 40.

Bailey and Meurers (2008), Created a dataset (CREE reading comprehension) for language learners and automated short answer scoring systems. The corpus consists of 566 responses from intermediate students. Mohler and Mihalcea (2009). Created a dataset for the computer science domain consists of 630 responses for data structure assignment questions. The scores are range from 0 to 5 given by two human raters.

Dzikovska et al. (2012) created a Student Response Analysis (SRA) corpus. It consists of two sub-groups: the BEETLE corpus consists of 56 questions and approximately 3000 responses from students in the electrical and electronics domain. The second one is the SCIENTSBANK(SemEval-2013) (Dzikovska et al. 2013a; b) corpus consists of 10,000 responses on 197 prompts on various science domains. The student responses ladled with "correct, partially correct incomplete, Contradictory, Irrelevant, Non-domain."

In the Kaggle (2012) competition, released total 3 types of corpuses on an Automated Student Assessment Prize (ASAP1) (“https://www.kaggle.com/c/asap-sas/”) essays and
short answers. It has nearly 17,450 essays, out of which it provides up to 3000 essays for each prompt. It has eight prompts that test 7th to 10th grade US students. It gives scores between the [0–3] and [0–60] range. The limitations of these corpora are: (1) it has a different score range for other prompts. (2) It uses statistical features such as named entities extraction and lexical features of words to evaluate essays. ASAP + + is one more dataset from Kaggle. It is with six prompts, and each prompt has more than 1000 responses total of 10,696 from 8th-grade students. Another corpus contains ten prompts from science, English domains and a total of 17,207 responses. Two human graders evaluated all these responses.

Correnti et al. (2013) created a Response-to-Text Assessment (RTA) dataset used to check student writing skills in all directions like style, mechanism, and organization. 4–8 grade students give the responses to RTA. Basu et al. (2013) created a power grading data-set with 700 responses for ten different prompts from US immigration exams. It contains all short answers for assessment.

The TOEFL11 corpus Blanchard et al. (2013) contains 1100 essays evenly distributed over eight prompts. It is used to test the English language skills of a candidate attending the TOFEL exam. It scores the language proficiency of a candidate as low, medium, and high.

International Corpus of Learner English (ICLE) Granger et al. (2009) built a corpus of 3663 essays covering different dimensions. It has 12 prompts with 1003 essays that test the organizational skill of essay writing, and13 prompts, each with 830 essays that examine the thesis clarity and prompt adherence.

Argument Annotated Essays (AAE) Stab and Gurevych (2014) developed a corpus that contains 102 essays with 101 prompts taken from the essayforum2 site. It tests the persuasive nature of the student essay. The SCIENTSBANK corpus used by Sakaguchi et al. (2015) available in git-hub, containing 9804 answers to 197 questions in 15 science domains. Table 3 illustrates all datasets related to AES systems.

### Table 3  ALL types Datasets used in Automatic scoring systems

| Data Set                                         | Language | Total responses | Number of prompts |
|--------------------------------------------------|----------|----------------|-------------------|
| Cambridge Learner Corpus-First Certificate in English exam (CLC-FCE) | English  | 1244           |                   |
| CREE                                             | English  | 566            |                   |
| CS                                               | English  | 630            |                   |
| SRA                                              | English  | 3000           | 56                |
| SCIENTSBANK(SemEval-2013)                        | English  | 10,000         | 197               |
| ASAP-AES                                         | English  | 17,450         | 8                 |
| ASAP-SAS                                         | English  | 17,207         | 10                |
| ASAP + +                                         | English  | 10,696         | 6                 |
| power grading                                    | English  | 700            |                   |
| TOEFL11                                          | English  | 1100           | 8                 |
| International Corpus of Learner English (ICLE)    | English  | 3663           |                   |

3.2 RQ2 what are the features extracted for the assessment of essays?

Features play a major role in the neural network and other supervised Machine Learning approaches. The automatic essay grading systems scores student essays based on
different types of features, which play a prominent role in training the models. Based on their syntax and semantics and they are categorized into three groups. 1. statistical-based features Contreras et al. (2018); Kumar et al. (2019); Mathias and Bhattacharyya (2018a; b) 2. Style-based (Syntax) features Cummins et al. (2016); Darwish and Mohamed (2020); Ke et al. (2019). 3. Content-based features Dong et al. (2017). A good set of features appropriate models evolved better AES systems. The vast majority of the researchers are using regression models if features are statistical-based. For Neural Networks models, researches are using both style-based and content-based features. The following table shows the list of various features used in existing AES Systems. Table 4 represents all set of features used for essay grading.

We studied all the feature extracting NLP libraries as shown in Fig. 3, that are used in the papers. The NLTK is an NLP tool used to retrieve statistical features like POS, word count, sentence count, etc. With NLTK, we can miss the essay’s semantic features. To find semantic features Word2Vec Mikolov et al. (2013), GloVe Jeffrey Pennington et al. (2014)

### Table 4 Types of features

| Statistical features                                      | Style based features       | Content based features                           |
|----------------------------------------------------------|----------------------------|--------------------------------------------------|
| Essay length with respect to the number of words          | Sentence structure         | Cohesion between sentences in a document         |
| Essay length with respect to sentence                      | POS                        | Overlapping (prompt)                             |
| Average sentence length                                   | Punctuation                | Relevance of information                         |
| Average word length                                       | Grammatical                | Semantic role of words                           |
| N-gram                                                    | Logical operators          | Correctness                                      |
|                                                           | Vocabulary                 | Consistency                                      |
|                                                           |                            | Sentence expressing key concepts                 |

![Fig. 3 Usages of tools](image-url)
is the most used libraries to retrieve the semantic text from the essays. And in some systems, they directly trained the model with word embeddings to find the score. From Fig. 4 as observed that non-content-based feature extraction is higher than content-based.

3.3 RQ3 which are the evaluation metrics available for measuring the accuracy of algorithms?

The majority of the AES systems are using three evaluation metrics. They are (1) quadratic weighted kappa (QWK) (2) Mean Absolute Error (MAE) (3) Pearson Correlation Coefficient (PCC) Shehab et al. (2016). The quadratic weighted kappa will find agreement between human evaluation score and system evaluation score and produces value ranging from 0 to 1. And the Mean Absolute Error is the actual difference between human-rated score to system-generated score. The mean square error (MSE) measures the average squares of the errors, i.e., the average squared difference between the human-rated and the system-generated scores. MSE will always give positive numbers only. Pearson’s Correlation Coefficient (PCC) finds the correlation coefficient between two variables. It will provide three values (0, 1, −1). “0” represents human-rated and system scores that are not related. “1” represents an increase in the two scores. “−1” illustrates a negative relationship between the two scores.

3.4 RQ4 what are the Machine Learning techniques being used for automatic essay grading, and how are they implemented?

After scrutinizing all documents, we categorize the techniques used in automated essay grading systems into four baskets. 1. Regression techniques. 2. Classification model. 3. Neural networks. 4. Ontology-based approach.
All the existing AES systems developed in the last ten years employ supervised learning techniques. Researchers using supervised methods viewed the AES system as either regression or classification task. The goal of the regression task is to predict the score of an essay. The classification task is to classify the essays belonging to (low, medium, or highly) relevant to the question’s topic. Since the last three years, most AES systems developed made use of the concept of the neural network.

### 3.4.1 Regression based models

Mohler and Mihalcea (2009) proposed text-to-text semantic similarity to assign a score to the student essays. There are two text similarity measures like Knowledge-based measures, corpus-based measures. There eight knowledge-based tests with all eight models. They found the similarity. The shortest path similarity determines based on the length, which shortest path between two contexts. Leacock & Chodorow find the similarity based on the shortest path’s length between two concepts using node-counting. The Lesk similarity finds the overlap between the corresponding definitions, and Wu & Palmer algorithm finds similarities based on the depth of two given concepts in the wordnet taxonomy. Resnik, Lin, Jiang & Conrath, Hirst & St-Onge find the similarity based on different parameters like the concept, probability, normalization factor, lexical chains. In corpus-based likeness, there LSA BNC, LSA Wikipedia, and ESA Wikipedia, latent semantic analysis is trained on Wikipedia and has excellent domain knowledge. Among all similarity scores, correlation scores LSA Wikipedia scoring accuracy is more. But these similarity measure algorithms are not using NLP concepts. These models are before 2010 and basic concept models to continue the research automated essay grading with updated algorithms on neural networks with content-based features.

Adamson et al. (2014) proposed an automatic essay grading system which is a statistical-based approach in this they retrieved features like POS, Character count, Word count, Sentence count, Miss spelled words, n-gram representation of words to prepare essay vector. They formed a matrix with these all vectors in that they applied LSA to give a score to each essay. It is a statistical approach that doesn’t consider the semantics of the essay. The accuracy they got when compared to the human rater score with the system is 0.532.

Cummins et al. (2016). Proposed Timed Aggregate Perceptron vector model to give ranking to all the essays, and later they converted the rank algorithm to predict the score of the essay. The model trained with features like Word unigrams, bigrams, POS, Essay length, grammatical relation, Max word length, sentence length. It is multi-task learning, gives ranking to the essays, and predicts the score for the essay. The performance evaluated through QWK is 0.69, a substantial agreement between the human rater and the system.

Sultan et al. (2016). Proposed a Ridge regression model to find short answer scoring with Question Demoting. Question Demoting is the new concept included in the essay’s final assessment to eliminate duplicate words from the essay. The extracted features are Text Similarity, which is the similarity between the student response and reference answer. Question Demoting is the number of repeats in a student response. With inverse document frequency, they assigned term weight. The sentence length Ratio is the number of words in the student response, is another feature. With these features, the Ridge regression model was used, and the accuracy they got 0.887.

Contreras et al. (2018). Proposed Ontology based on text mining in this model has given a score for essays in phases. In phase-I, they generated ontologies with ontoGen and SVM to
find the concept and similarity in the essay. In phase II from ontologies, they retrieved features like essay length, word counts, correctness, vocabulary, and types of word used, domain information. After retrieving statistical data, they used a linear regression model to find the score of the essay. The accuracy score is the average of 0.5.

Darwish and Mohamed (2020) proposed the fusion of fuzzy Ontology with LSA. They retrieve two types of features, like syntax features and semantic features. In syntax features, they found Lexical Analysis with tokens, and they construct a parse tree. If the parse tree is broken, the essay is inconsistent—a separate grade assigned to the essay concerning syntax features. The semantic features are like similarity analysis, Spatial Data Analysis. Similarity analysis is to find duplicate sentences—Spatial Data Analysis for finding Euclid distance between the center and part. Later they combine syntax features and morphological features score for the final score. The accuracy they achieved with the multiple linear regression model is 0.77, mostly on statistical features.

Süzen Neslihan et al. (2020) proposed a text mining approach for short answer grading. First, their comparing model answers with student response by calculating the distance between two sentences. By comparing the model answer with student response, they find the essay’s completeness and provide feedback. In this approach, model vocabulary plays a vital role in grading, and with this model vocabulary, the grade will be assigned to the student’s response and provides feedback. The correlation between the student answer to model answer is 0.81.

3.4.2 Classification based Models

Persing and Ng (2013) used a support vector machine to score the essay. The features extracted are OS, N-gram, and semantic text to train the model and identified the keywords from the essay to give the final score.

Sakaguchi et al. (2015) proposed two methods: response-based and reference-based. In response-based scoring, the extracted features are response length, n-gram model, and syntactic elements to train the support vector regression model. In reference-based scoring, features such as sentence similarity using word2vec is used to find the cosine similarity of the sentences that is the final score of the response. First, the scores were discovered individually and later combined two features to find a final score. This system gave a remarkable increase in performance by combining the scores.

Mathias and Bhattacharyya (2018a; b) Proposed Automated Essay Grading Dataset with Essay Attribute Scores. The first concept features selection depends on the essay type. So the common attributes are Content, Organization, Word Choice, Sentence Fluency, Conventions. In this system, each attribute is scored individually, with the strength of each attribute identified. The model they used is a random forest classifier to assign scores to individual attributes. The accuracy they got with QWK is 0.74 for prompt 1 of the ASAS dataset (https://www.kaggle.com/c/asap-sas/).

Ke et al. (2019) used a support vector machine to find the response score. In this method, features like Agreeability, Specificity, Clarity, Relevance to prompt, Conciseness, Eloquence, Confidence, Direction of development, Justification of opinion, and Justification of importance. First, the individual parameter score obtained was later combined with all scores to give a final response score. The features are used in the neural network to find whether the sentence is relevant to the topic or not.

Salim et al. (2019) proposed an XGBoost Machine Learning classifier to assess the essays. The algorithm trained on features like word count, POS, parse tree depth, and
coherence in the articles with sentence similarity percentage; cohesion and coherence are considered for training. And they implemented K-fold cross-validation for a result the average accuracy after specific validations is 68.12.

### 3.4.3 Neural network models

Shehab et al. (2016) proposed a neural network method that used learning vector quantization to train human scored essays. After training, the network can provide a score to the ungraded essays. First, we should process the essay to remove Spell checking and then perform preprocessing steps like Document Tokenization, stop word removal, Stemming, and submit it to the neural network. Finally, the model will provide feedback on the essay, whether it is relevant to the topic. And the correlation coefficient between human rater and system score is 0.7665.

Kopparapu and De (2016) proposed the Automatic Ranking of Essays using Structural and Semantic Features. This approach constructed a super essay with all the responses. Next, ranking for a student essay is done based on the super-essay. The structural and semantic features derived helps to obtain the scores. In a paragraph, 15 Structural features like an average number of sentences, the average length of sentences, and the count of words, nouns, verbs, adjectives, etc., are used to obtain a syntactic score. A similarity score is used as semantic features to calculate the overall score.

Dong and Zhang (2016) proposed a hierarchical CNN model. The model builds two layers with word embedding to represents the words as the first layer. The second layer is a word convolution layer with max-pooling to find word vectors. The next layer is a sentence-level convolution layer with max-pooling to find the sentence’s content and synonyms. A fully connected dense layer produces an output score for an essay. The accuracy with the hierarchical CNN model resulted in an average QWK of 0.754.

Taghipour and Ng (2016) proposed a first neural approach for essay scoring build in which convolution and recurrent neural network concepts help in scoring an essay. The network uses a lookup table with the one-hot representation of the word vector of an essay. The final efficiency of the network model with LSTM resulted in an average QWK of 0.708.

Dong et al. (2017). Proposed an Attention-based scoring system with CNN + LSTM to score an essay. For CNN, the input parameters were character embedding and word embedding, and it has attention pooling layers and used NLTK to obtain word and character embedding. The output gives a sentence vector, which provides sentence weight. After CNN, it will have an LSTM layer with an attention pooling layer, and this final layer results in the final score of the responses. The average QWK score is 0.764.

Riordan et al. (2017) proposed a neural network with CNN and LSTM layers. Word embedding, given as input to a neural network. An LSTM network layer will retrieve the window features and delivers them to the aggregation layer. The aggregation layer is a superficial layer that takes a correct window of words and gives successive layers to predict the answer’s score. The accuracy of the neural network resulted in a QWK of 0.90.

Zhao et al. (2017) proposed a new concept called Memory-Augmented Neural network with four layers, input representation layer, memory addressing layer, memory reading layer, and output layer. An input layer represents all essays in a vector form based on essay length. After converting the word vector, the memory addressing layer takes a sample of the essay and weighs all the terms. The memory reading layer takes
the input from memory addressing segment and finds the content to finalize the score. Finally, the output layer will provide the final score of the essay. The accuracy of essay scores is 0.78, which is far better than the LSTM neural network.

Mathias and Bhattacharyya (2018a; b) proposed deep learning networks using LSTM with the CNN layer and GloVe pre-trained word embeddings. For this, they retrieved features like Sentence count essays, word count per sentence, Number of OOVs in the sentence, Language model score, and the text’s perplexity. The network predicted the goodness scores of each essay. The higher the goodness scores, means higher the rank and vice versa.

Nguyen and Dery (2016). Proposed Neural Networks for Automated Essay Grading. In this method, a single layer bi-directional LSTM accepting word vector as input. Glove vectors used in this method resulted in an accuracy of 90%.

Ruseti et al. (2018) proposed a recurrent neural network that is capable of memorizing the text and generate a summary of an essay. The Bi-GRU network with the max-pooling layer molded on the word embedding of each document. It will provide scoring to the essay by comparing it with a summary of the essay from another Bi-GRU network. The result obtained an accuracy of 0.55.

Wang et al. (2018a; b) proposed an automatic scoring system with the bi-LSTM recurrent neural network model and retrieved the features using the word2vec technique. This method generated word embeddings from the essay words using the skip-gram model. And later, word embedding is used to train the neural network to find the final score. The softmax layer in LSTM obtains the importance of each word. This method used a QWK score of 0.83%.

Dasgupta et al. (2018) proposed a technique for essay scoring with augmenting textual qualitative Features. It extracted three types of linguistic, cognitive, and psychological features associated with a text document. The linguistic features are Part of Speech (POS), Universal Dependency relations, Structural Well-formedness, Lexical Diversity, Sentence Cohesion, Causality, and Informativeness of the text. The psychological features derived from the Linguistic Information and Word Count (LIWC) tool. They implemented a convolution recurrent neural network that takes input as word embedding and sentence vector, retrieved from the GloVe word vector. And the second layer is the Convolution Layer to find local features. The next layer is the recurrent neural network (LSTM) to find corresponding of the text. The accuracy of this method resulted in an average QWK of 0.764.

Liang et al. (2018) proposed a symmetrical neural network AES model with Bi-LSTM. They are extracting features from sample essays and student essays and preparing an embedding layer as input. The embedding layer output is transfer to the convolution layer from that LSTM will be trained. Hear the LSRM model has self-features extraction layer, which will find the essay’s coherence. The average QWK score of SBLSTMA is 0.801.

Liu et al. (2019) proposed two-stage learning. In the first stage, they are assigning a score based on semantic data from the essay. The second stage scoring is based on some handcrafted features like grammar correction, essay length, number of sentences, etc. The average score of the two stages is 0.709.

Pedro Uria Rodriguez et al. (2019) proposed a sequence-to-sequence learning model for automatic essay scoring. They used BERT (Bidirectional Encoder Representations from Transformers), which extracts the semantics from a sentence from both directions. And XLnet sequence to sequence learning model to extract features like the next sentence in an essay. With this pre-trained model, they attained coherence from the essay to give the final score. The average QWK score of the model is 75.5.
Xia et al. (2019) proposed a two-layer Bi-directional LSTM neural network for the scoring of essays. The features extracted with word2vec to train the LSTM and accuracy of the model in an average of QWK is 0.870.

Kumar et al. (2019) Proposed an AutoSAS for short answer scoring. It used pre-trained Word2Vec and Doc2Vec models trained on Google News corpus and Wikipedia dump, respectively, to retrieve the features. First, they tagged every word POS and they found weighted words from the response. It also found prompt overlap to observe how the answer is relevant to the topic, and they defined lexical overlaps like noun overlap, argument overlap, and content overlap. This method used some statistical features like word frequency, difficulty, diversity, number of unique words in each response, type-token ratio, statistics of the sentence, word length, and logical operator-based features. This method uses a random forest model to train the dataset. The data set has sample responses with their associated score. The model will retrieve the features from both responses like graded and ungraded short answers with questions. The accuracy of AutoSAS with QWK is 0.78. It will work on any topics like Science, Arts, Biology, and English.

Jiaqi Lun et al. (2020) proposed an automatic short answer scoring with BERT. In this with a reference answer comparing student responses and assigning scores. The data augmentation is done with a neural network and with one correct answer from the dataset classifying reaming responses as correct or incorrect.

Zhu and Sun (2020) proposed a multimodal Machine Learning approach for automated essay scoring. First, they count the grammar score with the spaCy library and numerical count as the number of words and sentences with the same library. With this input, they trained a single and Bi LSTM neural network for finding the final score. For the LSTM model, they prepared sentence vectors with GloVe and word embedding with NLTK. Bi-LSTM will check each sentence in both directions to find semantic from the essay. The average QWK score with multiple models is 0.70.

### 3.4.4 Ontology based approach

Mohler et al. (2011) proposed a graph-based method to find semantic similarity in short answer scoring. For the ranking of answers, they used the support vector regression model. The bag of words is the main feature extracted in the system.

Ramachandran et al. (2015) also proposed a graph-based approach to find lexical based semantics. Identified phrase patterns and text patterns are the features to train a random forest regression model to score the essays. The accuracy of the model in a QWK is 0.78.

Zupanc et al. (2017) proposed sentence similarity networks to find the essay’s score. Ajetunmobi and Daramola (2017) recommended an ontology-based information extraction approach and domain-based ontology to find the score.

### 3.4.5 Speech response scoring

Automatic scoring is in two ways one is text-based scoring, other is speech-based scoring. This paper discussed text-based scoring and its challenges, and now we cover speech scoring and common points between text and speech-based scoring. Evanini and Wang (2013), Worked on speech scoring of non-native school students, extracted features with speech rater, and trained a linear regression model, concluding that accuracy varies based on voice pitching. Loukina et al. (2015) worked on feature selection from speech data and trained
SVM. Malinin et al. (2016) used neural network models to train the data. Loukina et al. (2017). Proposed speech and text-based automatic scoring. Extracted text-based features, speech-based features and trained a deep neural network for speech-based scoring. They extracted 33 types of features based on acoustic signals. Malinin et al. (2017). Wu Xixin et al. (2020) Worked on deep neural networks for spoken language assessment. Incorporated different types of models and tested them. Ramanarayanan et al. (2017) worked on feature extraction methods and extracted punctuation, fluency, and stress and trained different Machine Learning models for scoring. Knill et al. (2018). Worked on Automatic speech recognizer and its errors how its impacts the speech assessment.

3.4.5.1 The state of the art  This section provides an overview of the existing AES systems with a comparative study w. r. t models, features applied, datasets, and evaluation metrics used for building the automated essay grading systems. We divided all 62 papers into two sets of the first set of review papers in Table 5 with a comparative study of the AES systems.

3.4.6 Comparison of all approaches

In our study, we divided major AES approaches into three categories. Regression models, classification models, and neural network models. The regression models failed to find cohesion and coherence from the essay because it trained on BoW(Bag of Words) features. In processing data from input to output, the regression models are less complicated than neural networks. There are unable to find many intricate patterns from the essay and unable to find sentence connectivity. If we train the model with BoW features in the neural network approach, the model never considers the essay’s coherence and coherence.

First, to train a Machine Learning algorithm with essays, all the essays are converted to vector form. We can form a vector with BoW and Word2vec, TF-IDF. The BoW and Word2vec vector representation of essays represented in Table 6. The vector representation of BoW with TF-IDF is not incorporating the essays semantic, and it’s just statistical learning from a given vector. Word2vec vector comprises semantic of essay in a unidirectional way.

In BoW, the vector contains the frequency of word occurrences in the essay. The vector represents 1 and more based on the happenings of words in the essay and 0 for not present. So, in BoW, the vector does not maintain the relationship with adjacent words; it’s just for single words. In word2vec, the vector represents the relationship between words with other words and sentences prompt in multiple dimensional ways. But word2vec prepares vectors in a unidirectional way, not in a bidirectional way; word2vec fails to find semantic vectors when a word has two meanings, and the meaning depends on adjacent words. Table 7 represents a comparison of Machine Learning models and features extracting methods.

In AES, cohesion and coherence will check the content of the essay concerning the essay prompt these can be extracted from essay in the vector from. Two more parameters are there to access an essay is completeness and feedback. Completeness will check whether student’s response is sufficient or not though the student wrote correctly. Table 8 represents all four parameters comparison for essay grading. Table 9 illustrates comparison of all approaches based on various features like grammar, spelling, organization of essay, relevance.
| System                                      | Approach                                      | Dataset               | Features applied         | Evaluation metric and results |
|---------------------------------------------|-----------------------------------------------|-----------------------|--------------------------|-------------------------------|
| Mohler and Mihalcea in (2009)               | shortest path similarity, LSA regression model | ASAP Kaggle           | Word vector              | Finds the shortest path       |
| Niraj Kumar and Lipika Dey. In (2013)       | Word-Graph                                    | ASAP Kaggle           | Content and style-based features | 63.81% accuracy               |
| Alex Adamson et al. in (2014)               | LSA regression model                          | ASAP Kaggle           | Statistical features      | QWK 0.532                     |
| Nguyen and Dery (2016)                      | LSTM (single layer bidirectional)             | ASAP Kaggle           | Statistical features      | 90% accuracy                  |
| Keisuke Sakaguchi et al. in (2015)          | Classification model                          | ETS (educational testing services) | Statistical, Style based features | QWK is 0.69                   |
| Ramachandran et al. in (2015)               | regression model                              | ASAP Kaggle short Answer | Statistical and style-based features | QWK 0.77                     |
| Sultan et al. in (2016)                     | Ridge regression model                        | SciEntBank answers    | Statistical features      | RMSE 0.887                    |
| Dong and Zhang (2016)                       | CNN neural network                            | ASAP Kaggle           | Statistical features      | QWK 0.734                     |
| Taghipour and Ngl in (2016)                 | CNN + LSTM neural network                     | ASAP Kaggle           | Lookup table (one hot representation of word vector) | QWK 0.761                     |
| Shehab et al. in (2016)                     | Learning vector quantization neural network   | Mansoura University student’s essays | Statistical features      | correlation coefficient 0.7665 |
| Cummins et al. in (2016)                    | Regression model                              | ASAP Kaggle           | Statistical features, style-based features | QWK 0.69                     |
| Kopparapu and De (2016)                     | Neural network                                | ASAP Kaggle           | Statistical features, Style based | QWK 0.764                     |
| Dong, et al. in (2017)                      | CNN + LSTM neural network                     | ASAP Kaggle           | Word embedding, content based | QWK 0.764                     |
| Ajetunmobi and Daramola (2017)              | WuPalmer algorithm                            | ASAP Kaggle           | Statistical features      |                               |
| Siyuan Zhao et al. in (2017)                | LSTM (memory network)                         | ASAP Kaggle           | Statistical features      | QWK 0.78                      |
| Mathias and Bhattacharyya (2018a)           | Random Forest Classifier a classification model | ASAP Kaggle           | Style and Content based features | Classified which feature set is required |
| Brian Riordan et al. in (2017)              | CNN + LSTM neural network                     | ASAP Kaggle short Answer | Word embeddings          | QWK 0.90                      |
| System                                      | Approach                                      | Dataset                        | Features applied                                      | Evaluation metric and results |
|---------------------------------------------|-----------------------------------------------|--------------------------------|-------------------------------------------------------|-----------------------------|
| Tirthankar Dasgupta et al. in (2018)        | CNN - bidirectional LSTMs neural network      | ASAP Kaggle                    | Content and physiological features                    | QWK 0.786                   |
| Wu and Shih (2018)                          | Classification model                          | SciEntBank answers             | unigram_recall, unigram_precision, unigram_F_measure, log_bleu_recall, log_bleu_precision, log_bleu_F_measure, BLUE features | Squared correlation coefficient 59.568 |
| Yucheng Wang, etc. in (2018)                | Bi-LSTM                                       | ASAP Kaggle                    | Word embedding sequence                               | QWK 0.724                   |
| Anak Agung Putri Ratna et al. in (2018)     | Winnowing ALGORITHM                          | ASAP Kaggle                    | Word embedding sequence                               | 86.86 accuracy              |
| Sharma and Jayagopi (2018)                  | Glove, LSTM neural network                    | ASAP Kaggle                    | Hand written essay images                              | QWK 0.69                    |
| Jennifer O. Contreras et al. in (2018)      | OntoGen (SVM) Linear Regression               | University of Benghazi data set| Statistical, style-based features                      |                             |
| Mathias, Bhattacharyya (2018b)              | GloVe, LSTM neural network                    | ASAP Kaggle                    | Statistical features, style features                   | Predicted Goodness score for essay Accuracy 55.2 |
| Stefan Ruseti, et al. in (2018)             | BiGRU Siamese architecture                    | Amazon Mechanical Turk online research service. Collected summaries | Word embedding              |                             |
| Zining wang, et al. in (2018a)              | LSTM (semantic) HAN (hierarchical attention network) neural network | ASAP Kaggle                    | Word embedding                                         | QWK 0.83                    |
| Guoxi Liang et al. (2018)                   | Bi-LSTM                                       | ASAP Kaggle                    | Word embedding, coherence of sentence                  | QWK 0.801                   |
| System                          | Approach                                    | Dataset          | Features applied                                      | Evaluation metric and results                      |
|--------------------------------|---------------------------------------------|------------------|------------------------------------------------------|----------------------------------------------------|
| Ke et al. in (2019)            | Classification model                        | ASAP Kaggle      | Content based                                        | Pearson’s Correlation Coefficient (PC)-0.39        |
|                                |                                              |                  |                                                      | ME-0.921                                           |
| Tsegaye Misikir Tashu and      | Unsupervised learning–Locality Sensitivity  | ASAP Kaggle      | Statistical features                                  | root mean squared error                            |
| Horváth in (2019)             | Hashing                                    |                  |                                                      |                                                    |
| Kumar and Dey (2019)           | Random Forest                              | ASAP Kaggle short Answer | Style and content-based features                      | QWK 0.82                                           |
| Pedro Uria Rodriguez et al.    | BERT, Xlnet                                 | ASAP Kaggle      | Error correction, sequence learning                  | QWK 0.755                                          |
| (2019)                        |                                              |                  |                                                      |                                                    |
| Jiawei Liu et al. (2019)      | CNN, LSTM, BERT                             | ASAP Kaggle      | semantic data, handcrafted features like grammar     | QWK 0.709                                          |
|                               |                                              |                  | correction, essay length, number of sentences, etc   |                                                    |
| Darwish and Mohamed (2020)    | Multiple Linear Regression                 | ASAP Kaggle      | Style and content-based features                      | QWK 0.77                                           |
| Jiaqi Lun et al. (2020)       | BERT                                        | SemEval-2013     | Student Answer, Reference Answer                      | Accuracy 0.8277 (2-way)                            |
| Süzen, Neslihan, et al. (2020)| Text mining                                 | introductory computer science class in the University of North Texas, Student Assignments | Sentence similarity                                | Correlation score 0.81                             |
| Wilson Zhu and Yu Sun in       | RNN (LSTM, Bi-LSTM)                         | ASAP Kaggle      | Word embedding, grammar count, word count            | QWK 0.70                                           |
| (2020)                        |                                              |                  |                                                      |                                                    |
| Salim Yafet et al. (2019)     | XGBoost machine learning classifier         | ASAP Kaggle      | Word count, POS, parse tree, coherence, cohesion, type token ration | Accuracy 68.12                                      |
| Andrzej Cader (2020)          | Deep Neural Network                         | University of Social Sciences in Lodz students’ answers | asynchronous feature                                | Accuracy 0.99                                      |
| Tashu TM, Horváth T (2019)    | Rule based algorithm, Similarity based      | ASAP Kaggle      | Similarity based                                     | Accuracy 0.68                                      |
|                               | algorithm                                   |                  |                                                      |                                                    |
| System                        | Approach                                         | Dataset    | Features applied | Evaluation metric and results |
|-------------------------------|--------------------------------------------------|------------|------------------|-----------------------------|
| Masaki Uto(B) and Masashi Okano (2020) | Item Response Theory Models (CNN-LSTM,BERT) | ASAP Kaggle |                 | QWK 0.749                   |
| Essay | BoW << vector >> | Word2vec << vector >> |
|-------|-----------------|---------------------|
| Student 1 response | I believe that using computers will benefit us in many ways like talking and becoming friends with others through websites like facebook and myspace | << 0.00000 0.00000 0.165746 0.280633 ... 0.280633 0.280633 >> | << 3.9792988e-03 − 1.9810481e-03 1.9830784e-03 9.0381579e-04 − 2.9438005e-03 2.1778699e-03 4.4950014e-03 2.9508960e-03 − 2.2331756e-03 − 3.8774475e-03 3.5967759e-03 − 4.0194849e-03 − 3.0412588e-03 − 2.4055617e-03 4.8296354e-03 2.4813593e-03 ... − 2.7158875e-03 − 1.4563646e-03 1.4072991e-03 − 5.2228488e-04 − 2.3597316e-03 6.2979700e-04 − 3.0249553e-03 4.4125126e-04 2.1633594e-03 − 4.9487003e-03 9.9755758e-05 − 2.4388896e-03 >> |
| Student 2 response | More and more people use computers, but not everyone agrees that this benefits society. Those who support advances in technology believe that computers have a positive effect on people | << 0.26043 0.26043 0.153814 0.000000 ... 0.000000 0.000000 >> | << 3.9792988e-03 − 1.9810481e-03 1.9830784e-03 9.0381579e-04 − 2.9438005e-03 2.1778699e-03 4.4950014e-03 2.9508960e-03 − 2.2331756e-03 − 3.8774475e-03 3.5967759e-03 − 4.0194849e-03 − 3.0412588e-03 − 2.4055617e-03 4.8296354e-03 2.4813593e-03 ... − 2.7158875e-03 − 1.4563646e-03 1.4072991e-03 − 5.2228488e-04 − 2.3597316e-03 6.2979700e-04 − 3.0249553e-03 4.4125126e-04 2.1633594e-03 − 4.9487003e-03 9.9755758e-05 − 2.4388896e-03 >> |
From our study and results discussed in the previous sections, many researchers worked on automated essay scoring systems with numerous techniques. We have statistical methods, classification methods, and neural network approaches to evaluate the essay automatically. The main goal of the automated essay grading system is to reduce human effort and improve consistency.

The vast majority of essay scoring systems are dealing with the efficiency of the algorithm. But there are many challenges in automated essay grading systems. One should assess the essay by following parameters like the relevance of the content to the prompt, development of ideas, Cohesion, Coherence, and domain knowledge.

No model works on the relevance of content, which means whether student response or explanation is relevant to the given prompt or not if it is relevant to how much it is appropriate, and there is no discussion about the cohesion and coherence of the essays. All researches concentrated on extracting the features using some NLP libraries, trained their models, and testing the results. But there is no explanation in the essay evaluation system about consistency and completeness, But Palma and Atkinson (2018) explained coherence-based essay evaluation. And Zupanc and Bosnic (2014) also used the word coherence to evaluate essays. And they found consistency with latent semantic analysis (LSA) for finding coherence from essays, but the dictionary meaning of coherence is "The quality of being logical and consistent."

Another limitation is there is no domain knowledge-based evaluation of essays using Machine Learning models. For example, the meaning of a cell is different from biology to physics. Many Machine Learning models extract features with WordVec and GloVec; these NLP libraries cannot convert the words into vectors when they have two or more meanings.

### 3.5.1 Other challenges that influence the Automated Essay Scoring Systems.

All these approaches worked to improve the QWK score of their models. But QWK will not assess the model in terms of features extraction and constructed irrelevant answers. The QWK is not evaluating models whether the model is correctly assessing the answer or not. There are many challenges concerning students’ responses to the Automatic scoring system. Like in evaluating approach, no model has examined how to evaluate the constructed
Table 8 Comparison of all models with respect to cohesion, coherence, completeness, feedback

| Authors                          | Cohesion | Coherence | Completeness | Feedback |
|----------------------------------|----------|-----------|--------------|----------|
| Mohler and Mihalcea (2009)       | Low      | Low       | Low          | Low      |
| Mohler et al. (2011)             | Medium   | Low       | Medium       | Low      |
| Persing and Ng (2013)            | Medium   | Low       | Low          | Low      |
| Adamson et al. (2014)            | Low      | Low       | Low          | Low      |
| Ramachandran et al. (2015)       | Medium   | Medium    | Low          | Low      |
| Sakaguchi et al. (2015)          | Medium   | Low       | Low          | Low      |
| Cummins et al. (2016)            | Low      | Low       | Low          | Low      |
| Sultan et al. (2016)             | Medium   | Medium    | Low          | Low      |
| Shehab et al. (2016)             | Low      | Low       | Low          | Low      |
| Kopparapu and De (2016)          | Medium   | Medium    | Low          | Low      |
| Dong an Zhang (2016)             | Medium   | Low       | Low          | Low      |
| Taghipour and Ng (2016)          | Medium   | Medium    | Low          | Low      |
| Zupanc et al. (2017)             | Medium   | Medium    | Low          | Low      |
| Dong et al. (2017)               | Medium   | Medium    | Low          | Low      |
| Riordan et al. (2017)            | Medium   | Medium    | Low          | Low      |
| Zhao et al. (2017)               | Medium   | Medium    | Low          | Low      |
| Contreras et al. (2018)          | Medium   | Low       | Low          | Low      |
| Mathias and Bhattacharyya (2018a; b) | Medium   | Medium    | Low          | Low      |
| Mathias and Bhattacharyya (2018a; b) | Medium   | Medium    | Low          | Low      |
| Nguyen and Dery (2016)           | Medium   | Medium    | Low          | Low      |
| Ruseti et al. (2018)             | Medium   | Low       | Low          | Low      |
| Liu et al.(2018)                 | Low      | Low       | Low          | Low      |
| Wang et al. (2018b)              | Medium   | Low       | Low          | Low      |
| Guoxi Liang et al. (2018)        | High     | High      | Low          | Low      |
| Wang et al. (2018a)              | Medium   | Medium    | Low          | Low      |
| Chen and Li (2018)               | Medium   | Medium    | Low          | Low      |
| Li et al. (2018)                 | Medium   | Medium    | Low          | Low      |
| Alva-Manchego et al.(2019)       | Low      | Low       | Low          | Low      |
| Jiawei Liu et al. (2019)         | High     | High      | Medium       | Low      |
| Pedro Uria Rodriguez et al. (2019)| Medium   | Medium    | Medium       | Low      |
| Changzhi Cai (2019)              | Low      | Low       | Low          | Low      |
| Xia et al. (2019)                | Medium   | Medium    | Low          | Low      |
| Chen and Zhou (2019)             | Low      | Low       | Low          | Low      |
| Kumar et al. (2019)              | Medium   | Medium    | Medium       | Low      |
| Ke et al. (2019)                 | Medium   | Low       | Medium       | Low      |
| Andrzej Cader(2020)              | Low      | Low       | Low          | Low      |
| Jiaqi Lun et al. (2020)          | High     | High      | Low          | Low      |
| Wilson Zhu and Yu Sun (2020)     | Medium   | Medium    | Low          | Low      |
| Sützen, Neslihan et al. (2020)   | Medium   | Low       | Medium       | Low      |
| Salim Yafet et al. (2019)        | High     | Medium    | Low          | Low      |
| Darwish and Mohamed (2020)       | Medium   | Low       | Low          | Low      |
| Tashu and Horváth (2020)         | Medium   | Medium    | Low          | Medium   |
| Tashu (2020)                     | Medium   | Medium    | Low          | Low      |
irrelevant and adversarial answers. Especially the black box type of approaches like deep learning models provides more options to the students to bluff the automated scoring systems.

The Machine Learning models that work on statistical features are very vulnerable. Based on Powers et al. (2001) and Bejar Isaac et al. (2014), the E-rater was failed on Constructed Irrelevant Responses Strategy (CIRS). From the study of Bejar et al. (2013), Higgins and Heilman (2014), observed that when student response contain irrelevant content or shell language concurring to prompt will influence the final score of essays in an automated scoring system.

In deep learning approaches, most of the models automatically read the essay’s features, and some methods work on word-based embedding and other character-based embedding features. From the study of Riordan Brain et al. (2019), The character-based embedding systems do not prioritize spelling correction. However, it is influencing the final score of the essay. From the study of Horbach and Zesch (2019), Various factors are influencing AES systems. For example, there are data set size, prompt type, answer length, training set, and human scorers for content-based scoring.

Ding et al. (2020) reviewed that the automated scoring system is vulnerable when a student response contains more words from prompt, like prompt vocabulary repeated in the response. Parekh et al. (2020) and Kumar et al. (2020) tested various neural network models of AES by iteratively adding important words, deleting unimportant words, shuffle the words, and repeating sentences in an essay and found that no change in the final score of essays. These neural network models failed to recognize common sense in adversaries’ essays and give more options for the students to bluff the automated systems.

Other than NLP and ML techniques for AES. From Wresch (1993) to Madnani and Cahill (2018), discussed the complexity of AES systems, standards need to be followed. Like assessment rubrics to test subject knowledge, irrelevant responses, and ethical aspects of an algorithm like measuring the fairness of student response.

Fairness is an essential factor for automated systems. For example, in AES, fairness can be measure in an agreement between human score to machine score. Besides this, From Loukina et al. (2019), the fairness standards include overall score accuracy, overall score differences, and condition score differences between human and system scores. In addition, scoring different responses in the prospect of constructive relevant and irrelevant will improve fairness.

Madnani et al. (2017a; b). Discussed the fairness of AES systems for constructed responses and presented RMS open-source tool for detecting biases in the models. With this, one can change fairness standards according to their analysis of fairness.

From Berzak et al.’s (2018) approach, behavior factors are a significant challenge in automated scoring systems. That helps to find language proficiency, word characteristics (essential words from the text), predict the critical patterns from the text, find related sentences in an essay, and give a more accurate score.
| Approaches                          | Grammar | Style (Word choice, sentence structure) | Mechanics (Spelling, punctuation, capitalization) | Development | BoW (tf-idf) | relevance |
|------------------------------------|---------|----------------------------------------|---------------------------------------------------|-------------|--------------|-----------|
| Mohler and Mihalcea (2009)         | No      | No                                     | No                                                | No          | Yes          | No        |
| Mohler et al. (2011)               | Yes     | No                                     | No                                                | No          | Yes          | No        |
| Persing and Ng (2013)              | Yes     | Yes                                    | Yes                                               | No          | Yes          | Yes       |
| Adamson et al. (2014)              | Yes     | No                                     | Yes                                               | No          | Yes          | No        |
| Ramachandran et al. (2015)         | Yes     | No                                     | Yes                                               | Yes         | Yes          | Yes       |
| Sakaguchi et al. (2015)            | No      | No                                     | Yes                                               | Yes         | Yes          | Yes       |
| Cummins et al. (2016)              | Yes     | No                                     | Yes                                               | No          | Yes          | No        |
| Sultan et al. (2016)               | No      | No                                     | No                                                | No          | Yes          | Yes       |
| Shehab et al. (2016)               | Yes     | Yes                                    | Yes                                               | No          | Yes          | No        |
| Kopparapu and De (2016)            | No      | No                                     | No                                                | No          | Yes          | No        |
| Dong and Zhang (2016)              | Yes     | No                                     | Yes                                               | No          | Yes          | Yes       |
| Taghipour and Ng (2016)            | Yes     | No                                     | No                                                | No          | Yes          | Yes       |
| Zupanc et al. (2017)               | No      | No                                     | No                                                | No          | Yes          | No        |
| Dong et al. (2017)                 | No      | No                                     | No                                                | No          | No           | Yes       |
| Riordan et al. (2017)              | No      | No                                     | No                                                | No          | No           | Yes       |
| Zhao et al. (2017)                 | No      | No                                     | No                                                | No          | No           | Yes       |
| Contreras et al. (2018)            | Yes     | No                                     | No                                                | No          | Yes          | Yes       |
| Mathias and Bhattacharyya (2018a, 2018b) | No  | Yes                                    | Yes                                               | No          | No           | Yes       |
| Mathias and Bhattacharyya (2018a, 2018b) | Yes | No                                     | Yes                                               | No          | Yes          | Yes       |
| Nguyen and Dery (2016)             | No      | No                                     | No                                                | No          | Yes          | Yes       |
| Ruseti et al. (2018)               | No      | No                                     | No                                                | Yes         | No           | Yes       |
| Dasgupta et al. (2018)             | Yes     | Yes                                    | Yes                                               | Yes         | No           | Yes       |
| Liu et al. (2018)                  | Yes     | Yes                                    | No                                                | No          | Yes          | No        |
| Wang et al. (2018b)                | No      | No                                     | No                                                | No          | Yes          | Yes       |
| Guoxi Liang et al. (2018)          | No      | No                                     | No                                                | No          | No           | Yes       |
| Wang et al. (2018a)                | No      | No                                     | No                                                | No          | No           | Yes       |
| Approaches                                | Grammar | Style (Word choice, sentence structure) | Mechanics (Spelling, punctuation, capitalization) | Development | BoW (tf-idf) | relevance |
|-------------------------------------------|---------|----------------------------------------|--------------------------------------------------|-------------|--------------|-----------|
| Chen and Li (2018)                        | No      | No                                     | No                                               | No          | No           | Yes       |
| Li et al. (2018)                          | Yes     | No                                     | No                                               | No          | No           | Yes       |
| Alva-Manchego et al. (2019)               | Yes     | No                                     | No                                               | Yes         | No           | Yes       |
| Jiawei Liu et al. (2019)                  | Yes     | No                                     | No                                               | Yes         | No           | Yes       |
| Pedro Uria Rodriguez et al. (2019)        | No      | No                                     | No                                               | No          | Yes         | Yes       |
| Changzi Cai (2019)                        | No      | No                                     | No                                               | No          | No           | Yes       |
| Xia et al. (2019)                         | No      | No                                     | No                                               | No          | No           | Yes       |
| Chen and Zhou (2019)                      | No      | No                                     | No                                               | No          | No           | Yes       |
| Kumar et al. (2019)                       | Yes     | Yes                                    | No                                               | Yes         | Yes         | Yes       |
| Ke et al. (2019)                          | No      | Yes                                    | No                                               | Yes         | Yes         | Yes       |
| Andrzej Cader (2020)                      | No      | No                                     | No                                               | No          | No           | Yes       |
| Jiaqi Lun et al. (2020)                   | No      | No                                     | No                                               | No          | No           | Yes       |
| Wilson Zhu and Yu Sun (2020)              | No      | No                                     | No                                               | No          | No           | Yes       |
| Süzen, Neslihan, et al. (2020)            | No      | No                                     | No                                               | No          | No           | Yes       |
| Salim Yafet et al. (2019)                 | Yes     | Yes                                    | Yes                                              | No          | Yes         | Yes       |
| Darwish and Mohamed (2020)                | Yes     | Yes                                    | No                                               | No          | No           | Yes       |
Rupp (2018), has discussed the designing, evaluating, and deployment methodologies for AES systems. They provided notable characteristics of AES systems for deployment. They are like model performance, evaluation metrics for a model, threshold values, dynamically updated models, and framework.

First, we should check the model performance on different datasets and parameters for operational deployment. Selecting Evaluation metrics for AES models are like QWK, correlation coefficient, or sometimes both. Kelley and Preacher (2012) have discussed three categories of threshold values: marginal, borderline, and acceptable. The values can be varied based on data size, model performance, type of model (single scoring, multiple scoring models). Once a model is deployed and evaluates millions of responses every time for optimal responses, we need a dynamically updated model based on prompt and data. Finally, framework designing of AES model, hear a framework contains prompts where test-takers can write the responses. One can design two frameworks: a single scoring model for a single methodology and multiple scoring models for multiple concepts. When we deploy multiple scoring models, each prompt could be trained separately, or we can provide generalized models for all prompts with this accuracy may vary, and it is challenging.

4 Synthesis

Our Systematic literature review on the automated essay grading system first collected 542 papers with selected keywords from various databases. After inclusion and exclusion criteria, we left with 139 articles; on these selected papers, we applied Quality assessment criteria with two reviewers, and finally, we selected 62 writings for final review.

Our observations on automated essay grading systems from 2010 to 2020 are as followed:

- The implementation techniques of automated essay grading systems are classified into four buckets; there are 1. regression models 2. Classification models 3. Neural networks 4. Ontology-based methodology, but using neural networks, the researchers are more accurate than other techniques, and all the methods state of the art provided in Table 3.
- The majority of the regression and classification models on essay scoring used statistical features to find the final score. It means the systems or models trained on such parameters as word count, sentence count, etc. though the parameters extracted from the essay, the algorithm are not directly training on essays. The algorithms trained on some numbers obtained from the essay and hear if numbers matched the composition will get a good score; otherwise, the rating is less. In these models, the evaluation process is entirely on numbers, irrespective of the essay. So, there is a lot of chance to miss the coherence, relevance of the essay if we train our algorithm on statistical parameters.
- In the neural network approach, the models trained on Bag of Words (BoW) features. The BoW feature is missing the relationship between a word to word and the semantic meaning of the sentence. E.g., Sentence 1: John killed bob. Sentence 2: bob killed John. In these two sentences, the BoW is "John," "killed," "bob."
- In the Word2Vec library, if we are prepared a word vector from an essay in a unidirectional way, the vector will have a dependency with other words and finds the semantic relationship with other words. But if a word has two or more meanings like "Bank loan" and "River Bank," hear bank has two implications, and its adjacent words decide
the sentence meaning; in this case, Word2Vec is not finding the real meaning of the word from the sentence.

- The features extracted from essays in the essay scoring system are classified into 3 type's features like statistical features, style-based features, and content-based features, which are explained in RQ2 and Table 3. But statistical features, are playing a significant role in some systems and negligible in some systems. In Shehab et al. (2016); Cummins et al. (2016); Dong et al. (2017); Dong and Zhang (2016); Mathias and Bhattacharyya (2018a; b) Systems the assessment is entirely on statistical and style-based features they have not retrieved any content-based features. And in other systems that extract content from the essays, the role of statistical features is for only preprocessing essays but not included in the final grading.

- In AES systems, coherence is the main feature to be considered while evaluating essays. The actual meaning of coherence is to stick together. That is the logical connection of sentences (local level coherence) and paragraphs (global level coherence) in a story. Without coherence, all sentences in a paragraph are independent and meaningless. In an Essay, coherence is a significant feature that is explaining everything in a flow and its meaning. It is a powerful feature in AES system to find the semantics of essay. With coherence, one can assess whether all sentences are connected in a flow and all paragraphs are related to justify the prompt. Retrieving the coherence level from an essay is a critical task for all researchers in AES systems.

- In automatic essay grading systems, the assessment of essays concerning content is critical. That will give the actual score for the student. Most of the researches used statistical features like sentence length, word count, number of sentences, etc. But according to collected results, 32% of the systems used content-based features for the essay scoring. Example papers which are on content-based assessment are Taghipour and Ng (2016); Persing and Ng (2013); Wang et al. (2018a, 2018b); Zhao et al. (2017); Kopparapu and De (2016), Kumar et al. (2019); Mathias and Bhattacharyya (2018a; b); Mohler and Mihalcea (2009) are used content and statistical-based features. The results are shown in Fig. 3. And mainly the content-based features extracted with word2vec NLP library, but word2vec is capable of capturing the context of a word in a document, semantic and syntactic similarity, relation with other terms, but word2vec is capable of capturing the context word in a uni-direction either left or right. If a word has multiple meanings, there is a chance of missing the context in the essay. After analyzing all the papers, we found that content-based assessment is a qualitative assessment of essays.

- On the other hand, Horbach and Zesch (2019); Riordan Brain et al. (2019); Ding et al. (2020); Kumar et al. (2020) proved that neural network models are vulnerable when a student response contains constructed irrelevant, adversarial answers. And a student can easily bluff an automated scoring system by submitting different responses like repeating sentences and repeating prompt words in an essay. From Loukina et al. (2019), and Madnani et al. (2017b). The fairness of an algorithm is an essential factor to be considered in AES systems.

- While talking about speech assessment, the data set contains audios of duration up to one minute. Feature extraction techniques are entirely different from text assessment, and accuracy varies based on speaking fluency, pitching, male to female voice and boy to adult voice. But the training algorithms are the same for text and speech assessment.

- Once an AES system evaluates essays and short answers accurately in all directions, there is a massive demand for automated systems in the educational and related world. Now AES systems are deployed in GRE, TOEFL exams; other than these, we can deploy AES systems in massive open online courses like Coursera("https://coursera.
org/learn//machine-learning//exam”), NPTEL (https://swayam.gov.in/explorer), etc. still they are assessing student performance with multiple-choice questions. In another perspective, AES systems can be deployed in information retrieval systems like Quora, stack overflow, etc., to check whether the retrieved response is appropriate to the question or not and can give ranking to the retrieved answers.

5 Conclusion and future work

As per our Systematic literature review, we studied 62 papers. There exist significant challenges for researchers in implementing automated essay grading systems. Several researchers are working rigorously on building a robust AES system despite its difficulty in solving this problem. All evaluating methods are not evaluated based on coherence, relevance, completeness, feedback, and knowledge-based. And 90% of essay grading systems are used Kaggle ASAP (2012) dataset, which has general essays from students and not required any domain knowledge, so there is a need for domain-specific essay datasets to train and test. Feature extraction is with NLTK, WordVec, and GloVec NLP libraries; these libraries have many limitations while converting a sentence into vector form. Apart from feature extraction and training Machine Learning models, no system is accessing the essay’s completeness. No system provides feedback to the student response and not retrieving coherence vectors from the essay—another perspective the constructive irrelevant and adversarial student responses still questioning AES systems.

Our proposed research work will go on the content-based assessment of essays with domain knowledge and find a score for the essays with internal and external consistency. And we will create a new dataset concerning one domain. And another area in which we can improve is the feature extraction techniques.

This study includes only four digital databases for study selection may miss some functional studies on the topic. However, we hope that we covered most of the significant studies as we manually collected some papers published in useful journals.

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