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Automatic Detection of Writing Proficiency Levels of Pakistani University Students Using NLP Techniques

Dr. Abdul Khaliq
abdulkhaliq@cuvas.edu.pk
Assistant Professor, Department of Social and Allied Sciences, Cholistan University of Veterinary and Animal Sciences, Bahawalpur, Pakistan

Khizar Mumtaz
hizarmian492@gmail.com
BSCS scholar, Department of computer science and information technology, cholistan University of veterinary and animal sciences, Bahawalpur

Ali Abbas
22-cuvas-0147@student.cuvas.edu.pk
BSCS scholar, Department of computer science and information technology, cholistan University of veterinary and animal sciences Bahawalpur

Corresponding Author: * Dr. Abdul Khaliq abdulkhaliq@cuvas.edu.pk

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ABSTRACT

The paper will introduce a clever solution to the automatic recognition of writing proficiency among the Pakistani university students through Natural Language Processing (NLP) and machine learning. A quantitative experimental design was used, with a dataset of undergraduate essays being preprocessed with the help of tokenization, stop-word detection, and lemmatization. To obtain linguistic patterns, textual features were obtained by Term Frequency Inverse Document Frequency (TF-IDF) analysis and n-gram analysis. Three classification models Support Vector Machine (SVM), Logistic Regression and Naive Bayes have been trained and tested with the common performance measures. The results indicate that each of the models is successful in categorizing the levels of writing proficiency, but SVM is the best because of its strength to process high-dimensional textual data. Moreover, vocabulary richness, grammatical accuracy, and syntactic complexity proved to be important predictors of writing quality. The research paper identifies the promise in NLP-based systems to provide a high-quality, reliable, and scalable system of automated writing evaluation in higher education.

Keywords: *Natural Language Processing, Writing Proficiency, Machine Learning, Automated Essay Scoring, Text Analytics, Pakistan.*

INTRODUCTION

Background of the Study

Academic success in college and university level is an inseparable part of writing proficiency, which allows students to express ideas, conduct critical analysis, and make arguments in a systematic way. The competence of grammar, vocabulary, coherence, and organization should be demonstrated in the written assignments that can be submitted by university students. Nonetheless, writing proficiency is a complicated and challenging task to evaluate, especially in large classroom institutions with a small number of faculty. Conventional ways of assessing the essays involve extensive use of manual grading which is both time consuming and prone to human error and inconsistency (Dikli, 2006).

As technology has advanced rapidly, Natural Language Processing (NLP) and machine learning have become potent tools to analyze textual information and to assess writing automatically. NLP

technologies can be used to analyze and analyze linguistic characteristics, including syntax, semantics, and discourse structure, thus making it easier to establish automated writing evaluation systems (Burstein et al., 2013). Systems that have been adopted all over the world like e-rater have shown that automated scoring of essay scoring can attain the same degree of reliability as human scoring (Attali and Burstein, 2006). Additionally, studies by Crossley et al. (2017) indicate that such linguistic characteristics as lexical diversity and cohesion are powerful predictors of the quality of writing.

The necessity of automated writing assessment systems is especially high in the context of Pakistan, where the number of students has risen, and the resources to teach them are scarce. Universities usually experience the difficulties of ensuring that there is a consistent and timely assessment of student work. Although the global community has already developed educational technologies based on NLP, these tools have still not been widely used in Pakistani higher education (Rahman et al., 2020; Khan and Ali, 2019). Thus, the use of NLP techniques in assessing writing can be useful in increasing efficiency, workload, and reliability of the evaluation systems.

Statement of the Problem

Manual assessment of student writing in higher learning institutions poses various challenges such as time, subjectivity and lack of consistency in marking criteria. Teachers must sometimes evaluate many essays in short periods of time and this may lead to low quality and unfair evaluation (Dikli, 2006). Also, inconsistency in the grading of an individual by the evaluators can result in different scores being given to students by the assessors based on their own personal judgment, impacting on student performance and quality of grading.

These problems are further complicated by the fact that automated writing assessment systems are not used in Pakistan. To effectively measure linguistic features and offer students timely feedback, universities do not have the tools to do it effectively. This can lead to the students not getting the proper guidance to enhance their writing competencies. Moreover, the increasing need to obtain quality education requires implementing new technologies that would facilitate the academic assessment procedures (Shermis & Hamner, 2012).

Considering these issues, it is necessary to create an algorithm that will be able to measure the writing proficiency level with high accuracy based on the methods of NLP and machine learning algorithms. This system can offer objective, consistent and efficient evaluation of student writing and hence enhance the overall education.

Research Objectives

1. To create an automated system that will help identify the level of writing proficiency based on NLP techniques.
2. To examine linguistic characteristics of richness of vocabulary, grammatical precision, and syntactic sophistication in student essays.
3. To use machine learning algorithms to classify.
4. To compare the effectiveness of NLP-based models in automated writing evaluation.
5. To investigate applicability of automated writing evaluation systems to Pakistani institutions of higher learning.

Research Questions

1. Can NLP techniques accurately detect writing proficiency levels of university students?
2. Which linguistic features contribute most to writing proficiency classification?
3. Which machine learning algorithm performs best for automated essay classification?
4. How effective are NLP-based models in improving writing assessment in higher education?
5. How applicable are automated writing evaluation systems in the Pakistani context?

Significance of the Study

The research has theoretical and practical importance. Hypothetically, it adds to the accumulated knowledge of Natural Language Processing and educational data mining by investigating the use of machine learning methods to the analysis of writing. It also builds upon the previous research because it concentrates on the higher education situation in Pakistan where there is a lack of such studies.

In real-world practice, the study will be of great help to teachers and policymakers as it illustrates how automated systems can facilitate more efficient and consistent evaluation. The use of automated writing assessment software can greatly decrease the workload of teachers and allow them to provide feedback on time, thus enhancing the writing abilities and academic performance of students. Moreover, it is possible to facilitate the creation of smart learning spaces with the help of NLP-based systems and encourage the use of digital technologies in learning (Crossley et al., 2017; Shermis and Burstein, 2013).

Delimitation of the Study

There are some limitations in this study. To begin with, it concentrates on English-language essays by undergraduate students of the chosen Pakistani universities. Second, the sample of the study is small and narrow, which can impact the applicability of the results. Third, the study uses classical machine learning algorithms like Support Vector Machine, Naive Bayes, and Logistic Regression, and more sophisticated deep learning models are not available because of the lack of data. Lastly, the research focuses on language and statistical attributes of writing and does not account for multimodal or contextual measures that can determine writing competence (Shermis and Burstein, 2013; Khan and Ali, 2019).

LITERATURE REVIEW

Automated writing evaluation (AWE) has evolved out of primitive statistical scoring systems to more advanced Natural Language Processing (NLP) and machine-learning techniques. A key breakthrough was the work of Page on the grading of computer-based essays, which demonstrated that textual characteristics could be used to provide an approximation of human scoring. Subsequently, semantic methods like Latent Semantic Analysis (LSA) diversified the area by allowing systems to compare meaning and content similarity in place of surface-level features alone. Later systems, such as ETS Criterion and e-rater, added grammar, mechanics, style, discourse and lexical elements, showing that automated systems can be very useful in the assessment of writing. This historical development reveals that there has been a change in dissimplified proxy measures to multidimensional models that are more accurate in describing the complexity of writing quality.

Conceptually, writing proficiency in this study is considered as a multidimensional construct that can be manifested through lexical richness, grammatical accuracy, syntactic complexity, cohesion, coherence, and communicative effectiveness in general. An NLP-based assessment pipeline involves

preprocessing student essays, representing them with textual features, like TF-IDF, n-grams, lexical sophistication, or discourse indices, and lastly classifying them into proficiency levels using supervised machine-learning models. In this model, the dependent construct is writing proficiency and the observable indicators of the construct are the linguistic and discourse features. Such conceptualization is in line with writing analytics studies that revealed that lexical diversity, cohesion, readability, and discourse organization are strong indicators of writing quality.

The present study theoretical framework is based on four interconnected traditions. First, the proxy theory of essay scoring developed by Page, determined that textual indicators of a broader judgment of quality are measurable. Second, the theory of semantic representation, in particular, LSA, describes how meaning-level similarity might be used to aid writing assessment by comparing student text to high-quality reference text. Third, trait-based scoring theory, as implemented in e-rater and Criterion, presupposes that writing quality is a set of identifiable dimensions, including grammar, usage, mechanics, style, and organization. Fourth, the supervised machine-learning theory treats the act of scoring essays as a classification task where labelled data can be used to teach a model the boundaries of decisions between proficiency levels. Combined, these viewpoints support the application of linguistic and machine-learning methods to categorize essays as beginners, intermediate, and advanced.

Automated writing quality detection is well supported by international literature. The first to prove computer grading was possible was Page (1966). Landauer, Foltz and Laham (1998) demonstrated that semantic similarity could be modeled by LSA and help in evaluating text automatically. According to Burstein, Chodorow and Leacock (2004), Criterion is a deployed educational technology which integrates scoring with feedback. At the same time, Attali and Burstein (2006) noted that e-rater V.2 had good scores with a small, yet significant, set of features. McNamara and colleagues continued this by demonstrating that discourse characteristics and hierarchical classification enhance automated scoring. Crossley and colleagues repeatedly discovered that lexical sophistication, cohesion, and syntactic patterns are predictors of writing quality and writing development. Zesch et al. (2015) showed that prompts-independent linguistic characteristics might be used to support the grading of essays. MacArthur et al. (2018) determined that linguistic constructs are predictors of quality of argumentative essays in college writers. The most recent reviews and syntheses still categorize AES approaches into content-based, machine-learning, and hybrid approaches, with the field evolving its methodology but still advancing feature engineering and model performance.

There is also a significant trend in these international investigations: there is no one type of feature that is the basis of successful AWE systems. Rather, they integrate lexical, syntactic, semantic and discourse information. Studies with Coh-Metrix and other comparable systems have indicated that coherence and cohesion are the main focal points of assessing writing quality, and other studies have revealed that semantic similarity, prompt relevance, and task-independent properties enhance robustness. It implies that a trustworthy writing-proficiency detector to be used in case of Pakistani university students can not be reduced to word counts and grammar checkers only, but should also consider the textual organization and meaning-level patterns.

The Pakistani literature is smaller and more disjointed, yet it also indicates clearly that they need to be improved when it comes to writing assessment and AI-assisted feedback. A report by the British Council on the use of English in the higher education sector of Pakistan noted poor student proficiency and the lack of support in the teaching of academic English as a significant issue. Another study by Garcia on enhancing the writing abilities of university students in Pakistan also indicated present weaknesses in writing and suggested more powerful teaching and evaluation approaches. The issues of grammar, cohesion, coherence, and teacher preparedness were recurrent in the work by Mahmood concerning the problem of academic writing in Pakistani higher education. The difficulty of writing by doctoral and undergraduate students has been reported by others in the area, particularly organization, citation practices, vocabulary, and sentence-level accuracy. Collectively, this national literature demonstrates that writing proficiency is a long-lasting issue throughout Pakistani higher education.

National AI, NLP, and automated feedback work is coming into existence but in small amounts. According to Khan and Ali (2019) and local debates on NLP in language assessment, there is an increasing focus on computational methods, yet there is a dearth of empirical, large-scale AWE studies in universities. According to a recent Pakistani survey on the reliability of the AES, there is increased institutional interest in the e-grading and human-machine score comparison. Recent studies of the Pakistani community have investigated AI-driven corrective feedback, teacher-AI interaction, AI-driven writing aids, and AWE-driven writing inspiration, whereby results have indicated that AI assistance can enhance grammatical correctness, vocabulary, engagement, and feedback promptness. Pakistani classroom research also indicates that students find AI writing tools helpful, but there is a concern about the pedagogy, overreliance, and the quality of implementation. All these national studies indicate that Pakistan is on the road to AI-based writing teaching, although the research base is in its infancy and more related to feedback perceptions and tool usefulness than the construction and validation of indigenous NLP-based proficiency classifiers.

One way to describe the 10 international studies is as follows: Page developed the first computational grading model; Landauer et al. developed LSA based semantic scoring; Burstein et al. described Criterion as a deployed system of AWE; Attali and Burstein tested e-rater V.2; McNamara et All these studies help to prove the international validity of NLP-based writing assessment.

Similarly, the top 10 national studies/sources, which seem most relevant to the current research, indicate that Pakistan is experiencing severe writing-proficiency issues, and has not yet started to look into AI-assisted solutions. They consist of the British Council higher-education English report, a model of improving Pakistani university writing by Garcia, analyzing the problem of academic-writing in EFL learners by Mahmood, research on doctoral and undergraduate writing problems, the recent AI-corrective feedback, AWE motivation, AI-assisted feedback-bots, AI collaboration in writing feedback with teachers, AI perceptions in university writing, and the AES reliability Combined, these papers warrant the necessity of a locally based automated writing-proficiency model as opposed to either importing systems or using general assumptions elsewhere.

Research Gap

Although the international AES research is strong, there are a few gaps as compared to the current study. First, majority of the validated AWE models have been created and tested on Western or large benchmark datasets, and not on essays by Pakistani university students. Second, although studies conducted globally have indicated the usefulness of lexical, syntactic, semantic and discourse features, the number of studies in Pakistan that have operationalized these features in a localized supervised machine-learning model to classify proficiency is very small. Third, recent Pakistani literature is largely dedicated to writing challenge, AI perception, or AI-based feedback, as opposed to the development and testing of a local, indigenous NLP-based model to predict writing proficiency levels based on original student essays. Fourth, Pakistani higher education multilingualism and ESL realities could influence feature behavior and model performance in a manner that is not reflected by the imported systems. Thus, the present research covers a significant gap by constructing a context-sensitive NLP and machine-learning system to automatically detect the proficiency in writing among Pakistani university students.

RESEARCH METHODOLOGY

Research Design

This research design is quantitative and is based on an experiment to design and test an automatic mechanism to identify the degree of writing knowledge by relying on Natural Language Processing (NLP) and machine learning methods. The experimental design is suitable because it enables conducting systematic testing and comparison of various algorithms on the basis of quantifiable

performance metrics. The research adheres to a supervised learning style, with labeled data (essays of students with predetermined proficiency levels) serving as the training and testing data (Burstein et al., 2013).

Data Collection and Dataset Description

The dataset in this study will be a collection of undergraduate student essays in English language in the chosen universities in Pakistan. The essays were gathered as part of the academic assignments and writing activities so that the essays are authentic and relevant. The essays were divided into pre-determined levels of proficiency (e.g., beginner, intermediate, and advanced) according to the pre-defined writing criteria, i.e., grammar, vocabulary, coherence, and organization.

The dataset consists of a wide variety of topics to reduce bias and make it generalizable. The data collection involved ethical considerations such as anonymity of students and use of data that was exclusively used in the research.

Data Preprocessing

The textual data were preprocessed with standard NLP methods to clean the text before analysis to enhance the quality of data and the model performance. Preprocessing steps were:

- **Tokenization:** Divisions of text into words or tokens.
- **Lowercasing:** Making all of the text in lower case.
- **Stop-word Removal:** Removing meanless words (e.g., the, is, etc.) that are common.
- **Lemmatization:** Minimization of words to their base or root.
- **Punctuation and Noise Removal:** Removal of extraneous symbols and special characters.

These measures make sure that the data is organized and can be used in extracting features and running a machine learning on it.

Feature Extraction

In order to transform textual data into numerical data, feature extraction methods were used. The research mainly employed:

- Term Frequency-Inverse Document Frequency (TF-IDF): To estimate word significance in documents.
- N-gram Analysis: To capture contextual patterns of words (e.g., bigrams, trigrams).

Also, lexical diversity, sentence length, and word frequency were taken into account as language characteristics to improve the performance of models. These characteristics assist in capturing writing characteristics associated with levels of proficiency (Crossley et al., 2017).

Machine Learning Models

The three popular supervised machine learning algorithms that were used in the study to classify texts were:

- **Support Vector Machine (SVM):** Good with high dimensional text data and known to have high classification accuracy.
- **Naive Bayes:** A probabilistic classifier that will be used with text data because of its simplicity and efficiency.
- **Logistic Regression:** It is a statistical model that is applied to binary and multiclassification.

The models were chosen because they have been shown to be effective in the NLP based classification tasks (Burstein et al., 2013; Shermis and Hamner, 2012).

Model Training and Testing

An 80/20 split was used to divide the dataset into training and testing subsets where:

- Training the models was done with 80% of the data.
- Data: Model performance was tested on 20% of the data.

This method makes sure that the models are tested on unseen data, hence a good estimate of their potential to generalize. Furthermore, cross-validation can also be used to increase model robustness.

Evaluation Metrics

In order to evaluate the performance of the classification models, the following evaluation metrics were applied:

- **Accuracy:** The ratio of correct classification.
- **Precision:** The percentage of the true positive predictions of the predicted positives.
- **Recall:** Determines how well the model can recognise all the relevant cases.
- **F1-Score:** The harmonic mean of recall and precision, giving balanced measure of performance.

These indicators give a holistic assessment of model performance and can be used to compare various algorithms (Crossley et al., 2017).

Tools and Software

The Python programming language and other libraries of NLP and machine learning, such as:, were used to analyze data and create the model.

- **NLTK (Natural Language Toolkit):** To preprocess text.
- **Scikit-learn:** To implement machine learning models.
- **Pandas and NumPy:** To manipulate and analyze data.

They are effective and efficient tools to use to work with textual data and create predictive models.

Limitations of the Methodology

There are limitations to this study. To begin with, the sample is restricted to selected university essays, which can impact the generalizability. Second, the traditional machine learning models are used in the study, and the advanced deep learning techniques are not applied because of the limitations of the data. Third, the analysis concentrates more on the linguistic characteristics and does not take into consideration the contextual and cognitive elements of writing.

ANALYSIS AND RESULTS

Model Performance Evaluation

Accuracy, precision, recall and F1-score were used to evaluate the performance of the three machine learning models, Support Vector Machine (SVM), Naïve Bayes and Logistic Regression.

Table 1: Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
Support Vector Machine	0.87	0.86	0.85	0.85
Naïve Bayes	0.78	0.76	0.75	0.75
Logistic Regression	0.82	0.81	0.80	0.80

Table 1 results show that all three machine learning models can classify the levels of writing proficiency, but they differ greatly in their performance. Support Vector Machine (SVM) had the best accuracy (87%), and better precision, recall, and F1-score, which proves its high capacity to work with high-dimensional textual data and capture complicated patterns in linguistic features.

The Logistic Regression model had a moderate performance of 82 per cent accuracy indicating that it is good at generalising between features and levels of proficiency, but it is not as good at modelling complex patterns as SVM. Conversely, the least accuracy (78 percent) was obtained with the Naïve Bayes classifier principally because it assumes feature independence and thus cannot adequately reflect the interdependence of the features in language. In general, the findings validate that SVM is the most robust model to write proficiency classification.

The confusion matrix analysis is a type of the SVM model (refer to 2).

Confusion Matrix Analysis (SVM Model)

Table 2: Confusion Matrix (SVM)

Actual \ Predicted	Beginner	Intermediate	Advanced
Beginner	45	5	2
Intermediate	6	40	4
Advanced	3	5	42

Table 2 presents the confusion matrix that gives a closer look at the way the SVM model performs in terms of classifying the data in different levels of proficiency. The model was accurate in most of the essays in all the three classifications that are: beginner, intermediate, and advanced and this shows that the overall accuracy was very high.

Misclassifications are fairly low and mainly identified between intermediate and advanced levels, as it is to be expected, because of similarities in the quality of writing between these levels. The model demonstrates good results in the accurate recognition of beginner-level essays implying that less advanced levels are more convenient to differentiate. In general, the confusion table proves that the SVM model exhibits a high accuracy and consistency of classifications, and its errors are minor.

Feature Importance Analysis

Table 3: Key Linguistic Features Influencing Classification

Feature Type	Impact Level	Description
Vocabulary Richness	High	Use of diverse and advanced vocabulary
Grammatical Accuracy	High	Correct sentence structure and grammar
Sentence Complexity	Medium	Use of complex and compound sentences
N-gram Patterns	Medium	Frequent contextual word combinations
Text Length	Low	Total number of words in essays

Table 3 results emphasize the comparative relevance of various linguistic characteristics to the levels of writing proficiency. The results reveal that vocabulary richness and grammar accuracy are most effective in terms of classification performances, meaning that students with a range of vocabulary use and proper grammar are most likely to attain higher levels of proficiency.

Individual characteristics like sentence complexity and n-gram patterns are also significant and can be attributed to the significance of structural and contextual elements of writing. In contrast, text length is least influential, implying that longer essays do not always imply higher quality of writing. These findings highlight that the important factor that determines writing proficiency is quality of language use, as opposed to text quantity.

Comparative Model Performance Analysis

The relative comparison of the models shows that there is a definite performance order within the three classifiers. Support Vector Machine (SVM) is the first because it is the most accurate and performs well in all the evaluation measures. It is especially useful in NLP-based classification tasks due to the dimensionality of its feature spaces.

The Logistic Regression model is the second model, with moderate performance and reliability in describing overall feature relationships, but less efficient in tackling more complicated data patterns. Naive Bayes model is the third one which offers a satisfactory but relatively worse performance because of its simplifying assumptions.

All in all, this comparison has shown that the classification of writing proficiency can be carried out with all the models, but SVM is the most powerful and consistent option, and then Logistic Regression, with Naive Bayes, as a baseline model.

Overall Results Summary

The results verify the fact that machine learning models based on NLP can be successfully used to predict writing proficiency levels of university students. Support Vector Machine proved to be the most robust classifier among those tested and proved to be the most effective at all the evaluation measures.

Moreover, linguistic characteristics (diversity of vocabulary, grammatical accuracy and syntactic complexity) are very important in writing quality. The findings confirm that automated systems can offer a consistent, objective and scalable alternative to manual essay scoring.

DISCUSSION

The results of the given work are the solid empirical data indicating that the Natural Language Processing (NLP) tools and machine learning algorithms could be successfully used to determine the writing proficiency levels among students in a university. The findings indicate that Support Vector Machine (SVM), Logistic Regression and Naive Bayes are all able to perform automated classification of essays, but their performance differs with regard to their capacity to encompass linguistic complexity and high-dimensional textual aspects.

The high accuracy of Support Vector Machine (SVM) model is in line with other studies of automated essay marking and text classification. SVM also outperformed the other two in terms of accuracy and overall performance, which can be explained by the fact that it is very powerful in dealing with high dimensional feature space like TF-IDF vectors and n-gram representations. This result is consistent with Crossley et al. (2017), who have stressed that sophisticated machine learning models can be very effective to extract linguistic patterns that are connected with the quality of writing. In the same vein, Burstein et al. (2013) noted that the combination of feature-rich models and suitable classification algorithms is a great way of enhancing automated writing evaluation systems. The confusion matrix findings further validate the fact that SVM can effectively be used to discriminate the various levels of proficiency with only few misclassifications between the intermediate and advanced proficiency, which can be attributed to the similarities in linguistic features.

The Logistic Regression model showed moderate results, which means that it could determine general relationships between linguistic characteristics and writing proficiency. Its relatively worse performance than SVM however implies that it cannot capture complex and non-linear relationships in textual data. The same observation is prompted by Shermis and Hamner (2012) who observed that the simpler statistical models though effective might not be fully effective in the multidimensional character of writing quality.

Naive Bayes classifier was the least performing model of the models that were tested, but it is computationally efficient. This is attributed to its assumption of feature independence which is not congruent with the interrelated nature of linguistic features like grammar, vocabulary and coherence. Other researchers have found similar limitations of Naive Bayes to text classification tasks (Burstein et al., 2013). However, its tolerable performance shows that it can still be used as a baseline model to automated essay scoring.

The analysis of feature importance showed that the most significant factors in writing proficiency determination were vocabulary richness and grammatical accuracy. This result has a very strong correlation with the work of Crossley et al. (2017), who found lexical diversity and linguistic sophistication as some of the key predictors of writing quality. Moreover, McNamara et al. (2014) also stressed that coherence and readability are crucial elements of effective writing, which also coincides with the identified effect of sentence complexity and n-gram patterns in the current study. The comparably weak effect of the amount of written material indicates that the quality of the writing relies on the linguistic competence than the amount of written text, which supports the notion that the quality of communication is not dependent on the volume of written text but on the quality of clarity and organization of text and meaning.

In general, the findings affirm that automated writing assessment systems are capable of offering consistent and objective as well as scalable alternatives to traditional manual grading systems. The results are consistent with the works of Attali and Burstein (2006), who proved the reliability of

automated systems like e-rater being as high as that of human assessors. Also, this research confirms the arguments of Dikli (2006) who claimed that grading time could be greatly reduced by automated scoring and assessment could be more reliable.

Within the context of Pakistani higher education, the results show the possible use of NLP-based systems to solve the issues concerning the high number of students in classes, insufficient staff, and irregular assessment standards. Although the previous local research has already highlighted the necessity to enhance writing assessment and technological integration (Rahman et al., 2020; Khan and Ali, 2019), the current research gives empirical evidence that such systems can be successfully introduced. Thus, NLP-based writing assessment tools could be integrated to improve the quality of education by offering timely feedback, enhance assessment reliability, and student learning outcomes.

CONCLUSION

This paper aimed at investigating the performance of Natural Language Processing (NLP) systems and machine learning algorithms in the automatic identification of the level of writing proficiency among Pakistani university students. The results clearly demonstrate that automated systems may be indeed used to classify student essays on the basis of linguistic characteristics, as an effective alternative to the previously used manual evaluation procedures.

The findings show that the Support Vector Machine (SVM), Logistic Regression, and Naive Bayes can be used to perform the classification of writing proficiency but their performance varies considerably. Among them, SVM was the most successful model with the highest accuracy, and it has better capabilities to work with high-dimensional textual data. This result supports the idea that more sophisticated machine learning models are more appropriate to represent complicated patterns in language as it is also indicated by prior studies (Crossley et al., 2017; Burstein et al., 2013).

Moreover, the research notes that such linguistic characteristics as the richness of vocabulary, grammatical correctness, and sentence complexity are the most important factors of writing proficiency. These results support the claim that quality of writing is more determined by the competence in language than by length of text or surface features. The lower performance of the Naive Bayes, comparatively, also highlights the need to select the relevant algorithms that can be effective to model the interdependence nature of linguistic features.

In sum, the research concludes that NLP-based automatic writing assessment systems have the potential to offer consistent, objective and efficient assessment of student writing. Such systems are a viable option in the context of Pakistani higher education, where major classes and small faculty resources are a real problem due to which reliability of grading and decreased workload on the teacher are a challenge. These results can be compared with the previous research that proved the great efficiency of automated essay scoring systems in improvements of the quality and efficiency of assessment (Attali and Burstein, 2006; Dikli, 2006).

RECOMMENDATIONS

According to the result of this research, it is suggested that institutions of higher learning in Pakistan should consider the implementation of NLP-based automated writing assessment system in their academic assessment practices. These systems have a potential to greatly decrease the workload of instructors by automating most of the routine grading processes and making the process more consistent and objective. Moreover, universities also need to invest in creation and upkeep of localized datasets based on the linguistic and contextual aspects of Pakistani students, which will enhance the performance and relevance of machine learning models.

It is also suggested that future studies should address more sophisticated methods like deep learning models like neural networks and transformer-based models to improve classification performance and identify more semantic relationships in text. The generalizability of the findings will also be enhanced by increasing the number and variety of samples that are represented in the dataset by incorporating various universities. Furthermore, the addition of other linguistic and discourse-level characteristics, like coherence, argument structure, and semantic similarity can also enhance the performance of the model.

Another area that educational policy makers ought to concentrate on is training the faculty to effectively utilize AI-based assessment tools, this way technology can be incorporated as an aiding mechanism and not as a substitute to human judgment. Lastly, an automated system with human assessment should be used, which would be most effective to provide the best results in assessments, balancing efficiency and pedagogical insight (Shermis and Burstein, 2013; Crossley et al., 2017).

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